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Technical University of Crete

Artificial intelligence for downhole tools

By

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Abstract

Revolutionizing methods used currently in the upstream industry especially the activities that involves high risks, in terms of operation, investments, human lives and the environment. Therefore, the introduction of new technologies is only possible after a rigorous validation phase to ensure that health, safety and environmental (HSE) standards are adequately met and that technology will benefit companies in terms of investments. Despite the great caution in introducing new technologies, the oil and gas industry remains open to new technologies to optimize and streamline existing processes. The low oil price period and the Covid-19 restrictions made it very necessary for that industry to adapt to new technologies to cope with such challenges. Reviewing and applying artificial intelligence methods used or to be used in the industry is the main focus of this thesis.

In the first part of this work, history available in the literature of the two different industries (oil and gas and the artificial intelligence) will be compared throughout a timeline and how the two industries benefit from each other.

Subsequently, different case studies will be discussed in order to study the efficiency of AI in production and workover. The first case study is for a virtual flow meter which is a convenient substitute of physical sensors it uses available data in instrumented wells to predict other measurements (oil, water and gas flowrates). Since most oil and gas wells have a transient process which changes with the life of the well, it is probable that the virtual flow meter model is not valid for the entire life of the well, but only for a certain period of time.The model is run against a dataset generated from a physics-based software (Pipesim software) by building python codes which automates the Pipesim work and retrieve data not easy to be retrieved by the conventional software. The same code can be implemented to predict all ESP needed throughout the lifetime of the field by predicting the recommended ESP each time we vary reservoir and well conditions. Then, the data generated are used by another algorithm built for this thesis in order to set our virtual flow meter and predict multiphase flow rates.The virtual flowmeter is based on the readings of the ESP pump at the surface.The best model (MLP) was chosen after cross validation and hyperparameters tuning of each model. The final model showed us an accuracy of more than 99%. Then, a second case study using graphical model (Bayesian network) for predicting the root cause of ESP breakdown (or stoppage). it is based on Bayesian network for such prediction. The results match with the inspection done by the service company engineer where the current change in the motor caused that stoppage in the pump. Moreover, a third case study, describes a reinforcement learning technique used in order for a system to autonomously make decisions for injection well to keep the reservoir pressure in its optimal range while decreasing the cost. That model was able to reduce the cost by 57%.

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Dedication

Dedicated to my family who supported me during all the time I was working on this thesis.

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I would like to thank the company in Ecuador for sharing data privately and exclusivley for this work to be done and a big thank to my scientific advisor, Dr. Dimitris Marinakis, for his support and for giving me the opportunity to work on such an interesting and challenging project. Also, I would like to thank Prof. Gaganis for his help. Also, in this context, I would also like to thank Professor Nikos Pasadakis for all his great efforts during the course and for giving me that opportunity to be a part of this master and for delivering my thesis project.

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Last, but not least, I am grateful to my family who were always supporting me. Words cannot express anything on their behalf.

Joe El Khoury

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A thesis submitted to the committee members

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Chapter 1

1 AI and oil and gas industries background and literature

Currently, industries around the world are experiencing the fourth industrial revolution. This revolution is being driven by extraordinary growth in computer infrastructure, predictive techniques, data storage, and data processing capabilities. The fourth industrial revolution- sometimes referred to as version 4.0 attached to the various industry names- is fueled by the following enablers:

- Industrial Internet of Things (IIoT), which facilitates seamless connectivity among numerous devices in enterprises and businesses and enables collaborative decision making.

- Big Data technologies that efficiently store and process massive amounts of data.

- Cloud computing machines that leverage accelerated computing devices, such as graphics processing units (GPUs).

1.1 Overview about the industry

Digitization is not new to the oil and gas industry while the industry is mainly divided into 3 sectors:

- Upstream

- Midstream

- Downstream

Thus, computerized networked oil fields have been around since the late 1970s. [1.3] Over the past two decades, however the upstream oil and gas industry has seen an exponential increase in the use of real-time data and field control devices, resulting in numerous implementations of digital oilfields. These have proven valuable in increasing operational efficiency, optimizing production and maximizing hydrocarbons recovery.
Moreover, today the oil and gas industry is also undergoing a digital transformation, referred to as "Oil and Gas 4.0." On one hand, the operation of the oil and gas industry involves high risks, both in terms of life integrity and the environment.
On the other hand, the main focus of upstream oil and gas efforts is the exploration and subsequent production of hydrocarbons, whether liquid products such as crude oil or natural gas products or, as in the other types of reservoirs such as the Canadian oil sands, heavy products such as bitumen.

So, it starts with entering into contracts with landowners or buying access to exploration blocks offshore thus that access and permits can be put in place. Once the contracts are in place and environmental conditions are favorable, the heavy rigs begin drilling.

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Then, drilling equipment is moved into position based on where the geologists think the subsurface prospects are most promising, and drilling operations begin. Drilling is a long subject in itself and I won't go into the details here, but basically drilling activities produce or deliver the production well, the well from which hydrocarbons are to be extracted. Oil and gas are found all over the world in a variety of different basins and reservoirs, and they are generally divided into onshore and offshore, with resources located on land or over water and far from land.
Both onshore and offshore require a significant amount of money or capital to carry out the work. Companies raise capital and borrow funds to provide the oil and gas company with the resources it needs to complete the drilling contracts, hire the personnel, and organize the supply chain that delivers all the necessary goods and services.
It can take months or even years to get wells up and running. For example, a well to be drilled onshore in a mountainous area may take two years of planning before the wells are delivered and oil and gas is produced. Or offshore might take like 10 years. The characteristics of the oil and gas reservoir dictate the specifics of how the oil and gas product will be produced. The upstream industry is rich in contracts, paper documents define access to land, service contracts govern services for drilling, delivery of water and sand and provision of facilities, licensing agreements with governments govern how royalties for hydrocarbons are divided among the various investors in the project.

In addition to taxing authorities, exploration also includes the construction of production facilities once the well is placed. The well requires surface facilities to control the pressure coming from the underground reservoir as oil and gas make their way to the surface. Infrastructure is needed to capture the oil or gas and prevent it from flowing freely over land or into the air. Well completion refers to the construction of these surface facilities.

In addition to initiating production, the product is collected at the wellhead and flows into tanks or pipelines from where it is released to the market over time. Well production declines and at a point the industry must decide whether to sell, abandon or stimulate the well. At the production phase, once the well begins producing oil and gas, production and reservoir engineers continue to monitor the well's production trends. So as oil and gas fields mature, reservoir and well conditions continually change. As a result, production declines due to increased water content (proportion or percentage of water in the oil), inefficient lifting equipment, inadequate reservoir pressure support, or surface backpressure bottlenecks, among other factors. Reservoir and field decline can be caused by both declines in production from individual wells and rapid increases in inactive strings (non-producing wells).
Production engineers develop plans to maintain the flow of oil from the well by using techniques such as artificial lift. Artificial lift may use pumps (electric submersible pumps, suction rod pumps, etc.) or gas lift by injecting gas into the lower wellbore to increase or maintain oil and gas flow from the well. Also, to address the decline in production, new wells must be drilled or existing wells must be intervened. Other well intervention and workover activities may also be performed during production operations, such as replacing a completion to maintain flow from the well, squeeze cement, well integrity, fishing jobs and zone isolation to optimize and maintain oil production.
The role of the Production Engineer is to ensure that reservoir production occurs within the existing limits of the approved field development plan, including the number of wells, rig capacity, and expenditures. The responsibilities of a production engineer may include the following:

- Plan, collect, and interpret production monitoring data.

- Creating, maintaining, and exploiting well performance management models.

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- Establishing well operating ranges and target values.

- Identify, classify, implement, and evaluate production improvement opportunities, including well workovers.

Moreover, abandoned wells are capped and sealed so that they pose no further risk to society and no longer produce or leak fluids from the subsurface. Decommissioning and reclamation of surface infrastructure associated with abandoned oil facilities is a critical part of the industry.

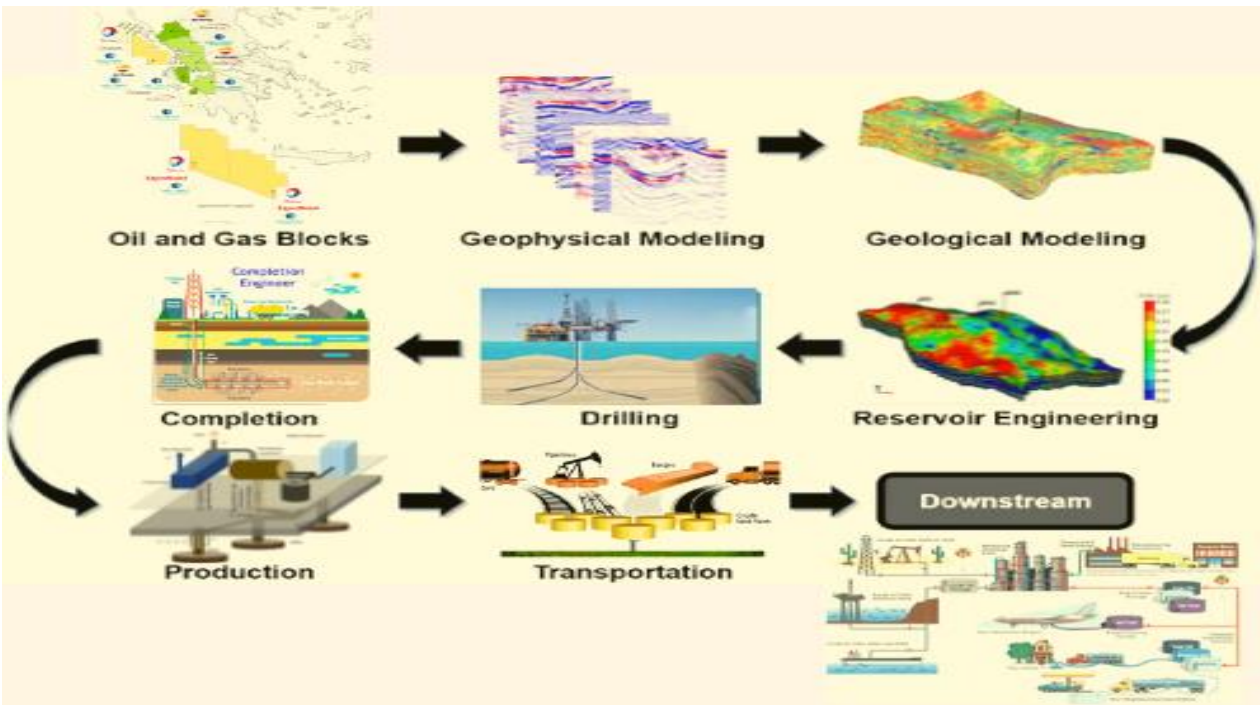

Figure 1. 1: showing all stages in an oil and gas field

So, logically upstream activities can be divided into the following areas:

- Exploration and appraisal

- Field development planning

- Drilling and completion

- Production

- -Abandonment

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1.2 Business problems

The most important concern for upstream companies is to:

1) Improve the performance of the most important asset, which is the underground reservoir. It is usually the largest asset on the balance sheet. It requires a tremendous amount of capital. The capital is usually at risk until the asset starts producing, and the value is at risk if the reservoir is abandoned or does not produce at the rate the owners expect.

   On one hand, the reservoirs that are currently most affected by digital innovation are the unconventional reservoirs. These are the reservoirs characterized by low porosity and low permeability that require fracking services to release the hydrocarbons to flow to the surface. The yield curves of these reservoirs, i.e. the amount of product that can be recovered from them, are behind those of conventional reservoirs or reservoirs with higher permeability and higher porosity. Many digital innovations, such as machine learning, have post-dated the development of fracking and horizontal drilling techniques.

   On the other hand, the typical recovery from a conventional basin is between 40 and 50 percent, meaning that 40 to 50 percent of the oil is actually recovered and 50 percent is left behind either because it's too expensive to recover the remaining 50 percent or because it's just too hard to get to due to the characteristics of the reservoir. In comparison, in tight reservoirs, recovery curves are in the 10 to 15 percent range. Thus, closing this gap will add 500 billion barrels of oil equivalent to resources and reserves.

2) Another important issue for companies is regulatory compliance and the environment. It is now widely recognized that fossil fuel consumption contributes to climate change. The oil and gas industry is facing more and more regulations related to fossil fuel emissions, CO_2 and methane, and water resource use. Governments everywhere are imposing strict new rules on the industry's performance. Thus, compliance and monitoring the impact of the industry's activities on the environment is a critical issue for the company. Hence, if a government declare that the industry will be denied access to water, an entire oil and gas basin that relies on access to water for fracking, for example, is suddenly stranded.

3) A final major area of concern is cost and labor management.

   When commodity prices rise, the cost of goods and services, as well as the labor costs that the industry consumes, rise at the same rate.

   When the price of oil goes from fifty dollars a barrel to a hundred dollars a barrel in a year, the price of goods and services in the industry also doubles as activity in the industry increases and bottlenecks occur.

1.3 Orthodoxies

The oil and gas industry has many undeclared rules that it follows that are generally accepted and typically go unchallenged. With the advent of digitization, many of these orthodoxies can now be confronted to see if they can be overturned or not. In another word, orthodoxies are patterns of thought or generally accepted rules or guidelines that an industry follows and that govern its behavior, decisions, and choices. Some of the orthodoxies in the upstream oil and gas industry that may or may not need to change as a result of digitalization as well:

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1) **Drilling takes priority**. The typical thought pattern in the oil and gas industry today is that if there is an opportunity to drill a well, you take it.

   So, the reason is that historically the value of the product has been so high and the margins have been so strong, and of course drilling has been steadily declining, that more production has always been the right answer. Simply producing more and of course converting assets from the balance sheet to production also drove that behavior.

   Thus, there may be much more value in the business, from improving productivity in some internal process.

2) **Allocation of resources**. given the scarcity of people and talent, the rule in the oil and gas industry is that you assign your people to the wells that bring the most value and leave the other wells unmanaged or at least unsupervised. That's changing as a machine with artificial intelligence may be able to monitor wells in addition to, or as well as, a human. Thus, the next step in the upstream is to manage well production like a project, much like a construction project or building in a city. Well production behaves very similarly, but digitization allows us to deliver the wells like a manufacturer.

3) **Maximize production as soon as a well is operational**, as soon as the equipment is in place, and as soon as the engineering work is complete. In a digital world, that may not make sense. Sometimes the cost of production exceeds the value of production. Under the current orthodoxy, we produce without regard to cost, and you don't shut down the well until it's clear that the cost of running the well for at least a year is not enough to cover the revenue generated. Digitization is changing that equation because we might be able to optimize production rather than maximize production. In the oil and gas industry, there is often a lack of visibility into how wells and the associated infrastructure around them are performing.

4) **Things are run until they stop working**, and then they will be fixed. Digitization allows us to keep track of wells with a granularity and transparency that we haven't had before, and that allows us to run wells until they're about to fail, and then schedule repairs to get them back online. That's much more cost effective than just running things until they stop working and then fixing them.

5) Last but not least, one of the key orthodoxies of the industry is that **work depends on people**. Many of the work processes in the oil and gas industry for delivering wells, maintaining wells, monitoring well infrastructure, depend entirely on a talented group of people to oversee and perform that work. This is largely a feature of the design of the infrastructure. However, the oil and gas industry is struggling to attract talents. The next generation of talented people may not be as interested in oil and gas as in the past, and the ability to attract talent to perform well site services is becoming an issue. Building infrastructure that is highly dependent on people is an orthodoxy in the industry and a constraint when there is a shortage of them.

Here is the digital framework with its layers:

- Artificial Intelligence,
- Robotics,
- Blockchain.

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1.4 Artificial intelligence

Artificial intelligence is used to interpret the data having sensors (or IOT) that will generate these data. Intelligence includes intelligent control which is a class of control techniques, that use various artificial intelligence (AI) computing approaches like neural networks, Bayesian probability, fuzzy logic, machine learning, evolutionary computation and genetic algorithms Intelligent control can be divided into the following major sub-domains:

- Neural network control
- Bayesian control (Bayesian networks)
- Fuzzy(logic) control (Neuro-fuzzy control)
- Expert Systems
- Genetic control, Differential evolution, Particle Swarm
- Intelligent agents (Cognitive/Conscious control)

The sheer volume and quantity of data has now thoroughly outpaced the old tools the industry used to work with. Thus, now the industry needs new tools to work with the sheer volume of data. Artificial intelligence encompasses a wide range of technologies. A.I. generally refers to specific human skills that are now available as a feature of machines. For example, it includes cameras that can interpret visual signals, sensors that interpret and translate spoken language, and speech generation.
So, Machine learning (which is division of artificial intelligence) requires enormous amounts of data. Hence, it involves teaching a machine to perform these human-like tasks. An example would be teaching a machine to recognize and distinguish between different patterns that might appear at the gate of a gas plant.
In the case of visual data, that means hundreds and hundreds of photos. For example, for a machine to learn the performance pattern of a pump, it takes millions and millions of pump performance cycles for the machine to recognize when a pump is malfunctioning in some way. Artificial intelligence is therefore a great fit for the oil and gas industry, as it already generates enormous amounts of data through its SCADA systems. The industry's operational activities run over very long periods of time. They are long-lived assets. They run 24/7, and the amount of information that is thrown off by the equipment is very, very large. This is far beyond the capacity of desktops and laptops, but is quite common in the upstream industry. These may not just be data sets generated by oil and gas, but also weather data sets, market data sets, consumer behavior data sets.

Moreover, AI can process and pull in multiple large data sets at once. Algorithms can run 24/7 and don't need brakes. Another feature is that for 24/7 operating algorithms. The self-learning or human learned algorithms can improve themselves and their accuracy. Hence, this self-improving functionality is very powerful and is one of the reasons why AI is very compliant with Metcalf's Law and Moore's Law.
An example would be when a pump needs to operate within a certain tolerance range, and an artificial intelligence algorithm is very well suited to monitor a number of data points coming from a large number of sensors on the pump and its performance, and make near-constant fine adjustments to ensure that the pump is constantly operating exactly within its optimal range. For example, if the pump is set in motion and running, and perhaps it deviates from acceptable performance, and then a human operator is called in to inspect and perhaps recalibrate the pump. Thus this takes lot of time and can interrupt the efficiency of some equipment. In the contrast, if an AI machine did that all the time. Thus, artificial

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intelligence (AI) is starting to make inroads into the realm of equipment control, such as plant pumps, jet pumps, compression equipment, artificial lift systems, turbines, anything that runs all the time and has the potential to benefit from fine-tuning every cycle.

Another important role for AI is interpretation of the subsurface. Although dealing with subsurface and seismic data is main to the oil and gas industry. So, the potential to apply these new tools to these older datasets is huge. Thus, in some studies, the International Energy Agency estimates that applying A.I. to some subsurface datasets, particularly the low-permeability, low-porosity datasets typical of upstream shale and tight sand reservoirs, will enable the industry to unlock an additional 5 percent of the world's reserves, equivalent to $ 22 trillion that is a very significant amount of money.

Another example in the oil and gas industry includes network optimization not only in simulation models but dynamically in near real time. there are many modifiable networks. think of multiple oil wells in an oil field connected to a production manifold or a series of flow lines, or a tank farm in an oil refinery with hundreds of tanks, or a downstream retail distribution network that distributes product by truck to resale points, and the requirement to optimize all tank capacity, product availability and delivery costs. Thus, a useful case is to improve data quality, especially older data sets AI by looking for outliers, filling in the gaps, and identifying data elements that are clearly not part of the normal data set and flagging them for human review. So, A.I. in the oil and gas industry will initially serve as a job wizard, and there are already many examples of this, assisting traders and people in the trading function with general operations and well monitoring, as well as predicting asset performance. A.I. will be valuable in data-rich, decision-intensive jobs for which there is a shortage of critical talent. These products optimize rigs that are currently unmanned or unattended on a regular basis, and they provide a high level of monitoring to these rigs. So, better interpretation of subsurface data means better understanding of the rigs The ability to predict performance by modeling oil and gas rigs under different constraints or scenarios so operators can take action to anticipate certain activities is a great feature of artificial intelligence machines and allows the industry to get ahead of problems before they occur.
This is the idea of a digital twin of a physical plant. It runs the digital version of a plant in the cloud through mathematics over multiple and even millions of cycles so that its performance can be much better understood and under a whole range of conditions.

1.5 Robotics

The last part of the core of digitalization is the workhorse: the **robots**, **automation** and **autonomy**.
If the Internet of Things generates data and the role of artificial intelligence is to interpret data, then the role of robots is to apply data. For example, today bots are present in at least two different contexts in the oil and gas industry:

1) In the front office we see drones, but in the back office there are many different classes and types. We see a technology called **robotic process automation**, or **RPA**. RPA first appeared in offshore shared service centers for human resources, accounting, and supply chain.

   These centers performed work processes that needed to be repeated over and over again, and software developers began to find ways to automate some of these routine back-office tasks.

   Out of this came a class of technology called RPA, which is now coming for the oil and gas

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industry. Document automation and document handling is a dramatic and powerful use case. Early adopters are seeing cost reductions in the 75 to 90 percent range. Automation in the back office, such as joint venture accounting and billing, royalty calculations, and anywhere there are routine, data-intensive, standardized calculations that repeat month after month, offers tremendous benefits

2) Robots are most applicable wherever **environments are dangerous**, remote and harsh:

   a) One example is the **underwater world**. Instead of sending divers to the ocean floor to perform certain types of service work on oil and gas infrastructure on the surface, oil and gas companies are now sending robots down. That's a **safety** issue, of course, and it saves money on human divers, because humans can only be on the seabed for short periods of time. Also, humans can't dive very deep, while robots can stay on the seabed for hours. So, seabed inspections are now very amenable to robotic roles.

   b) Another use case is routine and repetitive work in front office or in a harsh or hazardous environment.

      For example, the heavy haulers in Canadian oil sands mines, which are the trucks that transport bitumen from the mine to the separation plants, are now **unmanned transport vehicles or robots**. While the work is routine and repetitive. Such haulers originated in open pit mines in Australia. Wherever oil and gas operates a long-lived facility that runs 24/7 with routine and repetitive work in a harsh or hazardous environment, drones become very attractive. Also, safety has also been greatly improved by the use of robots, as they take humans out of harm's way

3) **For wells/plants inspection:** Drones can also help reduce costs significantly as they themselves run 24/7, which coincides with the cycle times of the plant not having shift changes, and can therefore reduce costs quite significantly. Also, it is important to make repairs to equipment and getting it back online quickly has significant value to the industry. For example, **Shell** uses drones to inspect wells from the air in Australia. Drones eliminate the need for an operator to drive around on the ground inspecting wells in a circle. So, the drone flies above the ground and performs the inspections from above. Also, robots for tank inspections and welding have been developed for the oil and gas industry for several years. Even when a tank is evacuated, there can still be fumes in it, especially during turnarounds and shutdowns. So, detecting a potential flare stack problem with the help of an inspection drone allows these plants to be repaired, returned to service, and kept in operation faster.

4) **For pipes inspection**: Pigs are inspection devices for pipelines. The pigs themselves are getting smarter and smaller through the use of nanotechnologies and are even becoming disposable. Thus, small robots can now work their way through very small diameter pipes and inspect them for cracks and corrosion, allowing pipeline owners to get ahead of problems.

5) **For logging**: An innovative idea called nano-logging. This idea was about the possibility of using nanorobots for logging applications. The inspiration came from the postulation of immune

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machines (nanomachines) capable of traveling through the human bloodstream to detect and destroy bacteria and viruses. Thus, they believed that the modification of this concept can be applied in the petroleum industry. Nanorobotics is about designing robots that have micron-scale dimensions but are equipped with nanometer-scale components. However, the nanorobots designed will have sizes on the order of centimeters. They provided strong arguments for the possibility that nanorobots could render measurement-while-drilling (MWD) and logging-while-drilling (LWD) technologies obsolete.

Since nanorobots are very small compared to conventional measurement devices, they can penetrate very close and deep into the formation, which enables the acquisition of more accurate drilling and formation parameters in real time. According to the authors (P. Singh, S. Bhat), they will not be operated as part of the drill string and will not be loaded as a source; therefore, there will be a large reduction in rig hours and logging costs. The nanorobot will be equipped with **nano-sensors** for information acquisition, **nanomotors** as a propulsion mechanism, a **carbon alloy shield** to protect the borehole, **microprocessors** to receive control information from the surface computer, and an **electromagnetic transmitter** to transmit data to the surface through electromagnetic waves. In addition, the nanorobot **can be transported through a mud circulation system**. A **special retrieval system placed in front of the shale shakers** or at the return point of the mud at the surface will catch the nanorobots at the surface. It also highlighted the few risks and challenges associated with the design and field deployment, but these can be circumvented. The risks mentioned were the incompetence or negligence of the personnel operating the nanorobots and the malfunction due to unexpected machine-machine interaction. The authors said that **fail-stop protocols** and **fail-safe design** as well as **personnel competence** are the ways to reduce these risks. Similarly, challenges related to nanorobots included their construction and mass production, programming and coordination, constant collision with downhole fluids, and recovery from the well. Further research and development in nanotechnology will help to overcome these challenges.

6) **Other researches**: Here some tools are/were under research for helping production engineers and the staff to take better decisions. Going to the beginning of the 21^{st} century the oil and gas industry has experienced some projects for autonomous tools using AI algorithms for making decisions which can perform real-time monitoring (Wireless tractor), workover and repairs without affecting too much the production, such as:

- Micro Rig (Halliburton and IIC)

- Bore rat (Baker Hughes and IIC)

- Autonomous tractoring (Welltec and BP)

- Autonomous perforating tool (ExxonMobil Upstream Research Co. with Hunting Energy Services' Titan division)

Noting that Welltec system didn't reach yet its final stage (not yet wireless) and for ExxonMobil tools they are planning to build more tools to increase intervention efficiency and well

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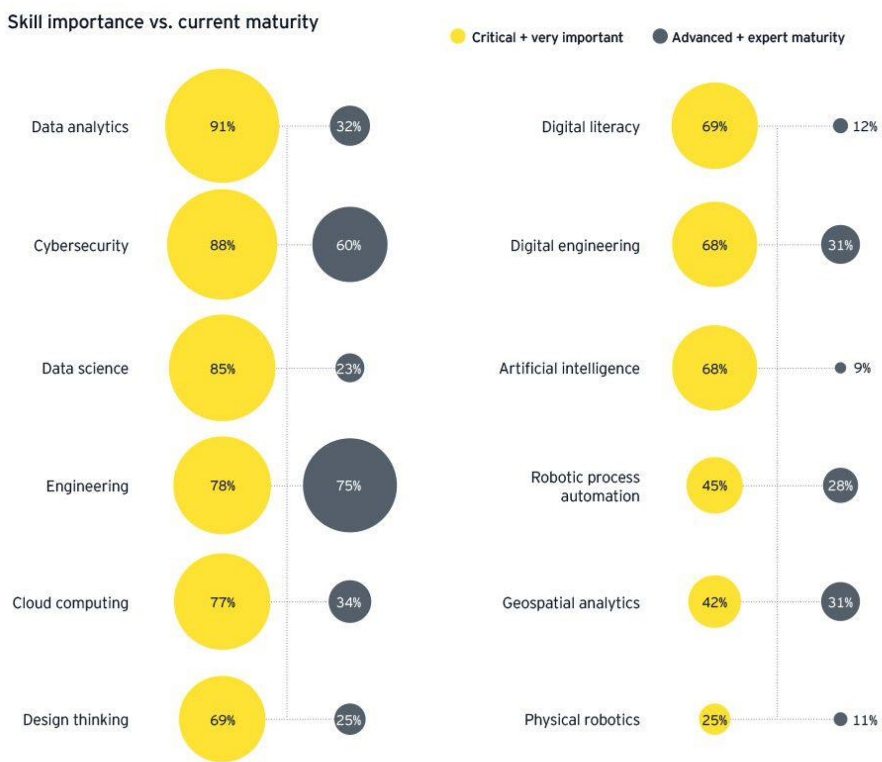
construction

1.6 Digital Twins

Some new emerging technologies tries to solve these problems and are relying on a new concept called digital twin in order to predict tools breakdown. Digital twins are able to mimic the operation of physical systems and use the data collected by their sensors to detect abnormal conditions and diagnose the cause of the problem. The concept of a digital twin (DT) and its application is not new. In the early stages of space missions, NASA developed exact physical copies of critical systems and used them to either simulate operations or replicate conditions to diagnose problems in actual systems. A DT is an evolution of this concept. With advances in digital modeling and increases in computing power, physical replicas have been replaced by sophisticated Multiphysics digital models. These digital replicas reflect with great accuracy the behavior of a physical system in every critical operational aspect. Digital twins model not only target the physical system, but also the surrounding environment. (Lastra, 2019) so the integration of real time data to the DT makes simulation dynamic in contrast to conventional simulators.

1.7 Technology for Upstream sector

So, Data, artificial Intelligence, robotics and cloud computing are the technologies that would be most disruptive to the upstream business model and address and tackle the issues raised before



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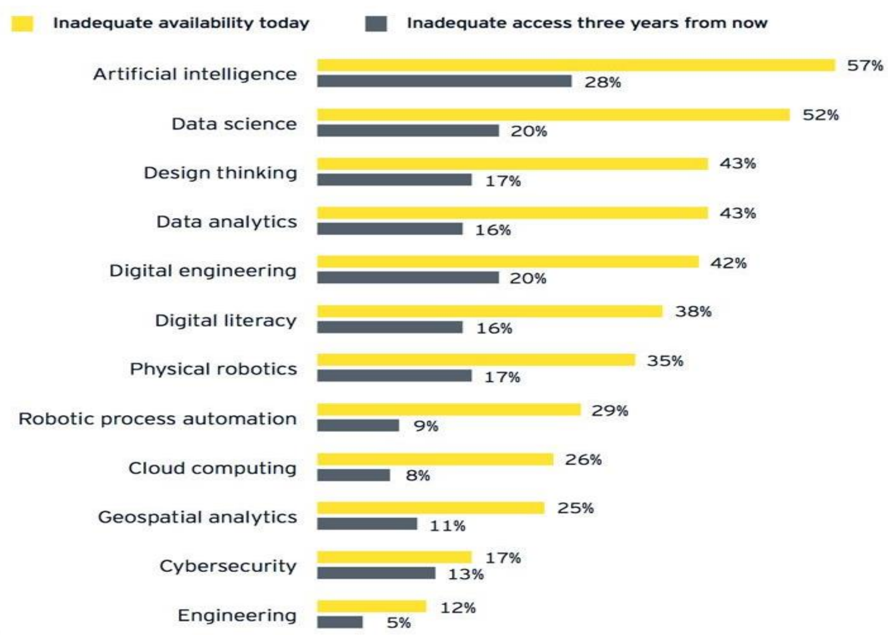

Figure 1. 2 -1.3: showing a report conducted in 2020 concluding that companies need to adapt and upskill their workforce if they want to be successful in enabling their digital transformation agenda according to the chart above in oil and gas sector maturity level according to consultancy.asia [1.1]

From the above figures, it can be concluded that the need for artificial intelligence and data analysis is very important in the oil and gas industry. So, the above technologies will have the biggest impact on the industry. Also, It can be deduced that there is a need to improve yields by applying artificial intelligence to the interpretation of subsurface data and a better understanding of permeability and porosity. That's the role of artificial intelligence. So, machine learning applied to this vast collection of subsurface data will be a critical feature of future digital solutions for the upstream. Moreover, it is important to increase productivity and reduce the cost of resources working in the industry. For that to work, there is a need to introduce a much higher level of automation and get better insight into what people are doing and the work they are already doing. Upstream leaders are targeting the use of autonomous technologies and robotic process automation to reduce the amount of work that is inherent in the business model.
In addition, it is important to lower new plant construction. Plant construction is one of the slowest activities in this industry, and accelerating the delivery of built infrastructure is critical. By that it doesn’t mean drilling wells faster. On one hand, the industry is doing a great job of improving well delivery, but it is the construction of many other assets, pipelines, storages and gas plants that take time. Also, the construction industry itself is not very digital. On the other hand, introducing digital innovation into the construction sector will be a lever to drive down costs.

Moreover, the next point is to optimize the service for managing wells. Again, cloud computing creates a space for service companies providing services to oil and gas to collaborate on a common platform or environment where service companies and owner operators can work more closely together. Finally, the use of robots to monitor under-managed wells. This is now being seen in both Canada and the United States. The industry is applying automation tools and artificial intelligence to the operation of fields of wells, not just individual wells, so that they operate in an optimized manner. Early results suggest that machines are outperforming humans at this task. This is a big change and something that is potentially very disruptive for oil and gas companies operating large portfolios of wells.

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1.8 Digitization impact and opportunities

1.8.1 Digitization impact on upstream business model

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Analytics, artificial intelligence, and machine tools that have been used successfully in other sectors are now being applied to the subsurface.
For example, **Enersoft**, a Calgary-based company, combines high-resolution photographs of drill cuttings with an inexpensive cellphone camera and machine learning to combine the photos and create a detailed digital version of the reservoir in the cloud, at the granularity level of a grain of sand. That's a million times higher granularity than what's traditionally found using seismic data to build and understand the subsurface.

1.8.2 Opportunities for small companies

So, it is an opportunity if many small oil and gas companies pooled their subsurface data and subjected it to machine learning algorithms in the cloud.
While small companies may have a lot of data themselves, it may not be enough to give them the kind of powerful analytics that are only available to really big oil companies.
By pooling their data in the cloud, many small companies can gain access to better quality analytics.
This could transform the economics and valuations of small companies.
And next, robotic processing automation (RPA) everywhere. Robotic processing tools have the potential to remove huge amounts of cost from the industry. Early adopters are already seeing cost reductions in the 90 to 95 percent range when robotic processing systems are deployed. These tools are not used as much in the front office, upstream drilling operations, as they are in the back office of the oil and gas industry. But the benefits are still significant.

1.9 Overview of digitization

1.9.1 Introduction

Today, this is largely a human endeavor where well productivity is low, there is not enough human talent to take care of the wells because human attention is just too costly, but robots controlled by an artificial intelligence machine can actually match or exceed the performance of human operators.
This will fundamentally change the way we think about oil and gas company design to use much more AI, machine learning, and robotics. At the same time, digital oilfield implementations enables better and faster decision-making while reducing health, environmental and safety risks. The digital oilfield is a process of a measurement-computation-control cycle with a frequency that maintains optimal system operating conditions at all times within the system's time constants, while sustainably

- Maximizing production
- Minimizing capital expenditures (CAPEX) / operating expenditures (OPEX)
- Minimizing the environmental impact
- Ensuring the safety of the people involved and the integrity of the associated equipment.[1.6][1.7]

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These goals can be achieved by synchronizing four interrelated areas:

- People
- Automated Operations
- Processes
- Technologies

It is an orchestration of disciplines, data, applications and workflow integration tools supported by digital automation that includes:

- Field instrumentation and telemetry
- Automation and Data management
- Integrated production models
- Predictive analytics
- Workflow automation
- Visualization
- Collaboration Environments

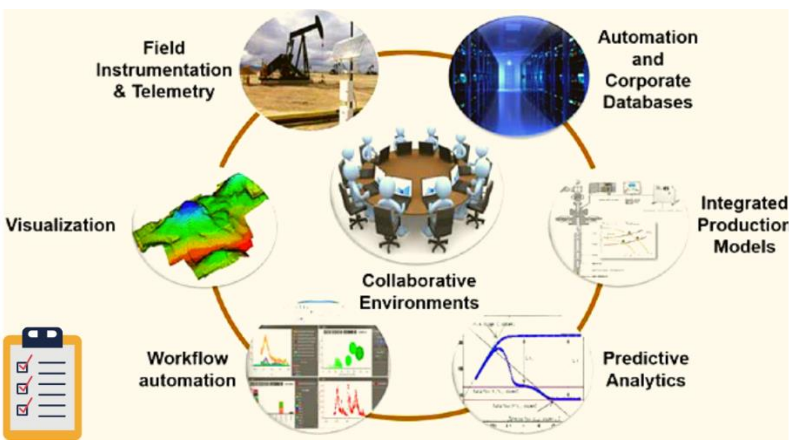

Figure 1.4: showing digital oil field different steps

Successful implementation of a digital oilfield requires synchronization between all these components. The predictive analytics component of a digital oilfield is responsible for generating data-driven insights about current and future oilfield prospects. This component often hosts machine learning algorithms and is key to the successful implementation of a digital oilfield. In the next section, we discuss how machine learning provides predictive analytics capabilities to digital oilfield implementations and the oil and gas industry as a whole

As we mentioned before that the upstream industry has been using machine learning since 1970s. However, it has been referred to as artificial intelligence or by other alternative names. The following figure shows a timeline for both machine learning milestones and the oil and gas industry. In the timeline, oil and gas industry milestones that represent advances in data collection and digitization have

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been highlighted. Based on the type of progress in the timeline, we can divide the timeline into different periods. The period up to the first decade of the 20th century is the basis for both industries.

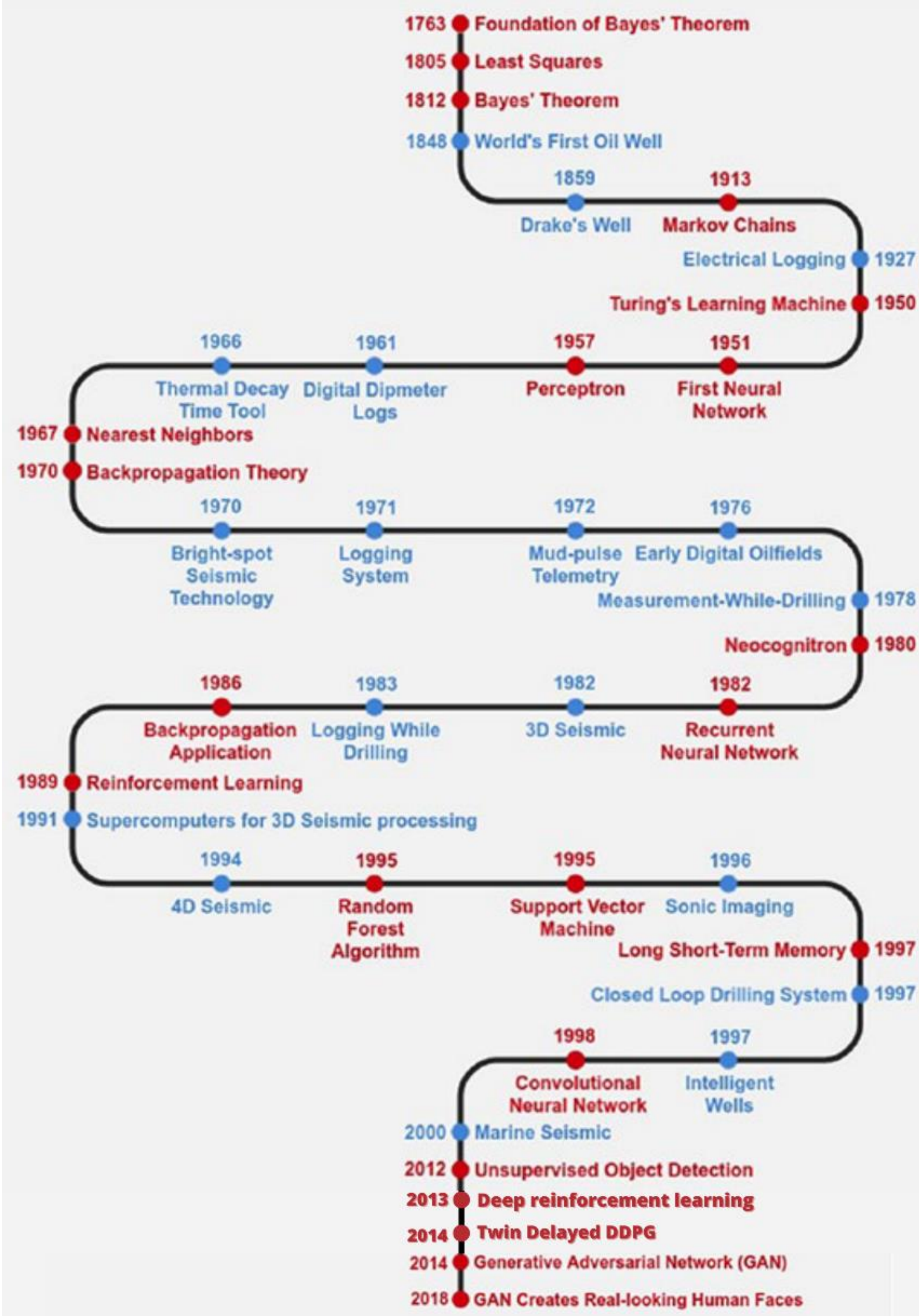

Figure 1.5: showing the timeline of the oil and gas industry with AI industry [1.4] [1.5]

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1.9.2 Timeline of AI and oil and gas industry discussion

In the early years, fundamental theoretical discoveries such as:

- Bayes' theorem
- the method of least squares

took place in the field of machine learning.
In the oil and gas industry, the first commercial oil wells were drilled, and oil gained popularity as a major fuel, slowly replacing coal fired steam engines.

In the mid-twentieth century, we observe the use of electric logging in the oil and gas industry. In contrast, Turing's learning machine appears shortly after the appearance of the first general purpose computer (ENIAC, 1945). The 1950s mark two very important discoveries in the field of machine learning which are the neural networks and perceptrons. Both are considered the foundation for the powerful advanced machine learning algorithms developed in the second half of the 20th century. The 1960s marked some important advances in the oil and gas industry, including digital dipmeters (which could record the angle of inclination in a well and help distinguish between different types of rock strata). Moreover, the 1960s also saw the invention of the Nearest-Neighbors algorithm, which is one of the fundamental machine learning algorithms. Moving on, we see several significant developments in the oil and gas industry during the 1970s.
Some of the significant technologies, such as:

- bright spot seismic,
- logging systems,
- mud pulse telemetry,
- and measurement-while-drilling (MWD),

emerged during this decade.

All of these technologies were significant developments in data acquisition and remain among the most important data sources for petroleum engineers today.
The first conceptualizations and implementations of digital oilfields took place in this decade, integrating various information platforms through computer systems.
For machine learning, backpropagation theory emerged. In the 1980s, 3D seismic changed forever the way geoscientists studied subsurface structures. Around the same time, logging-while-drilling (LWD) allowed access to real-time data during drilling operations and provided precise information about the physical properties of the subsurface formation. In the same decade, the invention of the Neocognitron laid the foundation for advanced computer vision, and the recurrent neural network (RNN) created a new tool for sequence modeling. It can only be a coincidence that one of the most important advances in 3D seismic imaging of the subsurface and the discovery of the fundamental computer vision algorithm neocognitron were a few years apart. Only two years apart in two different industries, can be linked to provide insights into the structure of the Earth's subsurface by applying computer vision algorithms to the seismic images. Two other significant discoveries in the field of machine learning in the 1980s were:

- the application of backpropagation theory to simplify neural network training
- the justification of reinforcement learning. Where reinforcement learning is one of the machine learning paradigms that relies on reward functions to train software agents to complete specific

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tasks. These are the algorithms that can teach a virtual gamer to win a game against a human (like in chess,..etc.), or teach a robot to walk like a human.

The 1990s saw significant advances in earthquake engineering. On the one hand, supercomputers were used to process 3D seismic data. On the other hand, 4D seismic data helped geoscientists interpret and visualize the evolution of subsurface structures over time. This was also a decade of another beautiful coincidence. As geoscientists gained the ability to understand the evolution of seismicity in a time sequence, machine learning found a new algorithm called Long Short Memory (LSTM) for sequence prediction. These two events are marked on the timeline only three years apart. LSTM addressed some limitations in conventional recurrent neural networks and enabled better sequence prediction capability. In the 1990s, the Random Forest and Support Vector Machine algorithms were also discovered. Over time, the Random Forest algorithm has earned a place among the go-to algorithms of any machine learning user. The 1990s was a decade of accelerated research in machine learning, and one of the fascinating algorithms published during that decade was the convolutional neural network (CNN).
CNNs have been a driving force in the field of computer vision over the past decade. The 1990s also saw new technologies in the oil and gas industry, such as:

- sonic logging,
- closed-loop drilling systems,
- smart wells.

In the twenty-first century, the oil and gas industry has seen significant technological advances in the area of data collection.
In addition to the vast amounts of data captured by offshore seismic surveys, the boom in the unconventional oil and gas industry has also produced large amounts of data. In addition, advances in computer hardware, such as computers based on graphics processing units (GPUs), have greatly accelerated computing power. By using fast computer hardware in conjunction with enormous amounts of training data, machine learning algorithms developed in recent years are able to identify objects in images and videos without human supervision. On the other hand, a new class of algorithms, generative adversarial network (GAN), is capable of generating human faces that are almost indistinguishable from real human images. Interestingly, GANs are also effectively used in seismic image reconstruction. [1.8]
Reviewing the milestones of the two industries, it is evident that both industries have collectively made significant progress in data acquisition, digitization, and the ability to learn from vast amounts of data.
Noting that the twin delayed DDPG is a new upgrade for deep reinforcement learning which is normally used on training new robots which can be used for the robots used on platforms and for new tools but still not well used in the industry- briefly it is a faster method than the deep reinforcement learning (which is upgrade to conventional q-learning techniques). Thus, twin delayed DDPG has higher accuracy using 2 twins of critic-actor systems with BP in order to train the model and learn fast.

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1.10 Artificial intelligence capabilities

In addition to the previous applications and opportunities using artificial intelligence. A more generalized capabilities can be divided as follow:

- Detect problems in system performance
- Diagnose the cause of problems
- Provide recommendations for correcting problems
- Estimate the remaining useful life of the system
- Ability to make autonomous and semi-autonomous operational changes to the system

Machine learning can be used in the following work during the production phase of the reservoir:

1) Identifying production issues with probabilities of occurrence for workover:

   Under certain circumstances, a well may not operate and produce satisfactorily during its life. Identifying such wells and implementing intervention and remedial actions (also called workovers) to bring well performance to satisfactory levels has demonstrated significant economic impact. Expert systems have been used in the oil and gas industry for decades, with processes ranging from data integration and cleansing to problem identification and ranking of candidates based on production gain, cost, risk and net present value. Novel systems using data analytics, machine learning, and inferential tools such as Bayesian Belief Networks have been proposed and used to identify production issues with probabilities of occurrence for various problems in wells, reservoirs, or facilities.[1.9][1.10] These systems help in differentiating the causes and prioritizing various countermeasures. These screening logics work as a repeatable and automated process that can be scheduled or run on demand.

2) Optimizing production

   The goal of production optimization is to profitably manage and ensure plant goals are met by using all the information available up to that point to confidently predict outcomes, make decisions that lead to optimal results, and implement those decisions by the next decision point.[1.11] The increasing availability of real-time downhole measurements and remotely controlled valves in oilfields has made real-time, field-wide optimization of operations a distinct possibility. With more real-time data and measurements, it is possible to build machine learning models that can be updated as new data becomes available. While the term real-time optimization (RTO) is certainly not new and RTO is practiced in elements of production operations, the extent to which RTO is now possible in daily production operations has increased dramatically.

3) Infill Drilling

   Infill drilling refers to additional drainage locations selected at a later stage of the field development cycle to increase the well's contact area with the reservoir. The objective of infill wells is to accelerate or improve recovery factors of wells that may have bypassed oil and gas reservoirs in their drainage area. The selection of infill well candidates requires careful analysis to verify, quantify and locate such bypassed reservoirs. Numerous data-driven methods have been developed to forecast production for potential sidetracks and provide a set of criteria for selecting

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the most appropriate well for a sidetrack, taking into account all associated uncertainties and linking them to a stochastic economic analysis.[1.12]

4) Optimal Completion Strategy

Completion is a term used to describe the hardware used downhole to ensure production from the reservoir to the wellhead. An optimal completion strategy requires proper understanding of reservoir potential (i.e., multiphase fluids, solids, productivity, and pressure regime as a function of time) and production requirements (i.e., rate targets and wellhead pressure). Many authors use multivariate analysis, which includes multiple linear regression analysis and statistical models using multidisciplinary data such as petrophysical data (e.g., thickness, permeability, saturation), completion (e.g., pipe size, stimulation fluid, and fracture intensity), and production (e.g., pressure and multiphase flow test data). Traditionally, production-based models, such as well models with nodal analysis, are good enough to provide accurate predictive relationships for successful completions. In cases of unknown well failure or uncertain reservoir phenomena, data-driven models provide much better predictions than pure engineering models. In the last five years, there has been an explosion in the application of machine learning algorithms to predict completion performance in unconventional reservoirs[1.13][1.14]. Data-driven methods help operators select optimal completion parameters that positively impact production and are beneficial for reducing unit costs, such as plugging and perforating designs for cemented wells, rate of injection, volume and mass per lateral foot.[1.15]

5) Predictive maintenance

A wide variety of equipment is used in the upstream oil and gas industry. All equipment has an operating life before it finally fails. More than 90% of all producing oil wells require an artificial lift method to increase oil production. The electric submersible pump (ESP) is commonly used for artificial lift, making it a critical component for ensuring continuous oil production from wells.

Although they are among the critical equipment in upstream operations, ESPs have a significantly high failure rate.[1.16][1.17] These failures are often random and result in a loss of oil production from the wells. It is estimated that ESP failures result in hundreds of millions of barrels of lost or deferred oil production per year.

Some new techniques using AI were used in order to prevent or decrease the stoppage time. On of the techniques used in PCA or Principal component analysis. In addition, principal component analysis is a statistical technique that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. PCA stands for POSC Caesar Association and under its auspices develops open specifications to enable data and software interoperability. As a body, it participates in research and joint industry projects to develop reference data and semantic technology. [1.2 p. 96]. An impending failure often shows up as PCA data scattered away from the origin. Combining these predictions from machine learning-based models with engineering principles to detect ESP problems long before they occur and prescribe preventive measures can have a significant economic impact. [1.8] [1.19]

Another very important concept to apply is the usage of machine learning with artificial lift equipment in order to form virtual flow meters. Thus, it will increase production and decrease stoppages and thus increase profit of the operating companies. Thus, in this thesis we will first take a case study regarding the usage of AI in order to deduce approximate virtual multiphase flow rate from reading ESP surface measurements

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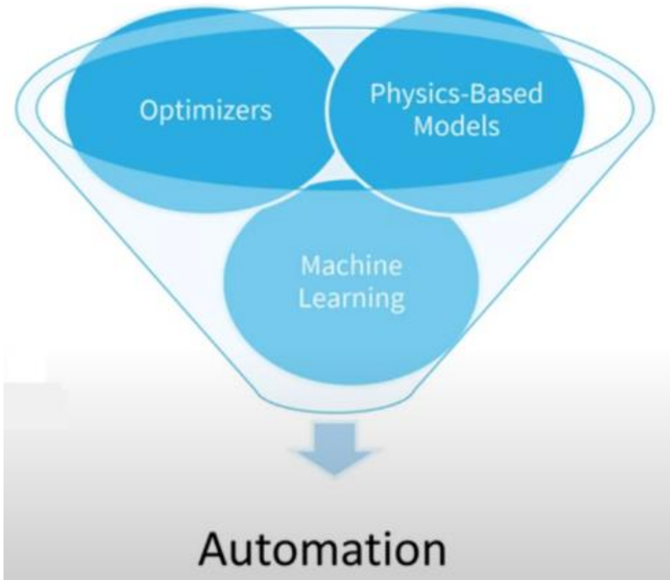

Figure 1. 6: Showing main components in order to have automation

1.11 Artificial intelligence algorithms literature

Artificial intelligence can be divided into different categories among these categories we can differentiate supervised, unsupervised and reinforcement learning. Also, a Bayesian network is another type of algorithm that is used in artificial intelligence.

1.11.1 Supervised learning

Machine learning algorithms are divided into different categories such as supervised, semi supervised, unsupervised and reinforcement learning techniques. In problems where a known input predicts the variable output fall under the category of supervised learning. If the output is quantitative or continuous, this leads to solving a regression problem. On the other hand, if the output is qualitative or discrete/categorical, it is a classification problem. [1.20] In other words, the goal is to learn a function f that represents the systematic information provided by the input variables to predict or make inferences about the response or dependent (output) variable. [1.21]

1.11.2 Regression

Regression is a subtype of supervised learning problems where the output is a quantitative or continuous variable. Thus, the goal of a regression problem is to find the optimal function f that can make accurate predictions of multiphase flow rates using all other variables as input characteristics.

1.11.2.1 Support Vector Regression

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Support vector regression is based on a support vector machine. In this method, the regression is performed for each point, allowing a margin of error. For each data point y, it is acceptable to obtain a predicted value in the range between ($y + \epsilon$) and ($y - \epsilon$). the error range ϵ is represented by two support vectors and allows flexibility in model tuning.
In addition to the error margin, this algorithm takes advantage of a kernel trick. The kernel trick projects a nonlinear lower-dimensional space onto a higher-dimensional space. In the higher dimensional space, it is possible to represent the original nonlinear problem as a linear problem.
In our case, Gaussian kernel (radial basis kernel), is selected because the dataset exhibits nonlinearity.

1.11.2.2 Ensemble learning

In real-world scenarios, a single model based on an algorithm may not provide the best solution.
Thus, the solution was to create multiple machine learning models trained with the same algorithm to produce a more powerful and robust predictive model. This is called Ensemble learning.
The idea is to combine multiple weak learners to create a strong learning ensemble that can provide higher accuracy than a single machine learning model. Bagging and boosting are two of the most common techniques in this category. They help in reducing noise, variance (i.e., avoiding overfitting) or bias (i.e., avoiding underfitting).
Before defining these concepts, it is important to understand bootstrapping, a resampling technique used in statistics. Bootstrapping involves randomly drawing multiple samples from a provided dataset with a replacement. A bootstrap can quantify the uncertainty associated with a statistical learning method.

1) Bagging is the short form of bootstrap aggregation. While high variance (overfitting) occurs in some machine learning algorithms, such as decision trees, bagging is extremely useful when homogeneous weak learners (i.e., models with poor performance) are combined through parallel training and a prediction is produced through an averaging process (regression) or voting process (classification). This process leads to a more robust model and reduces the risk of overfitting. In other words, bagging uses an equally weighted average to generate predictions, while boosting uses a composite of multiple learners to create a model with better performance.

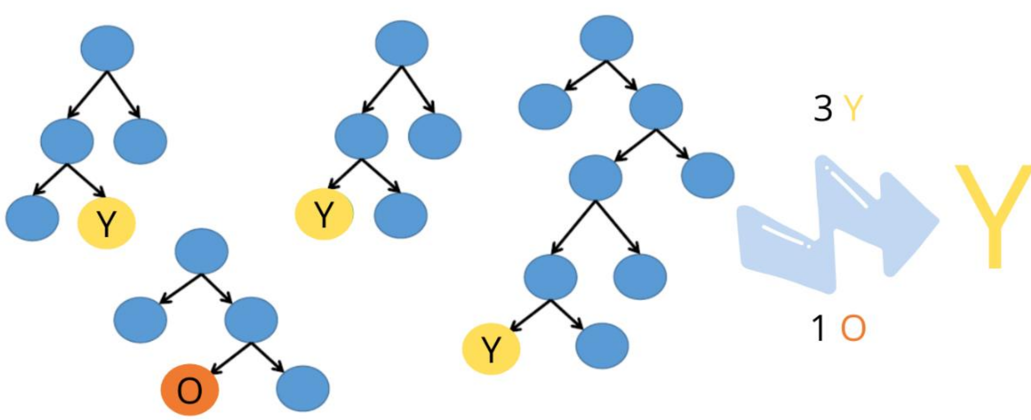

Figure 1. 7 showing how bagging in ensemble learning works.

2) Boosting, on the other hand, learns from an ensemble of homogeneous weak learners, but

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sequentially and adaptively. This approach attempts to minimize bias (underfitting) by training a model based on a previously trained model with poor performance, as opposed to reducing variance (overfitting) in bagging.

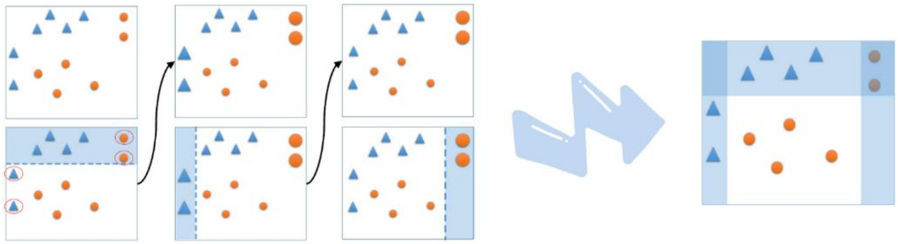

Figure 1. 8 showing how boosting in ensemble learning works.

1.11.2.2.1 Random Forest regression

In bagging aggregation belongs **Random Forest algorithm**, based on an ensemble of decision trees. This algorithm applies bagging, which was discussed earlier in this chapter. A random forest algorithm applies bagging to both the input features and the training data. This means that for each decision tree grown in a random forest model, a subset of the input features and the training data are randomly selected to train that decision tree. The algorithm trains multiple decision trees in parallel. The decision tree algorithm suffers from the problem of overfitting. This happens due to the use of a single tree that remembers almost all the training data and cannot generalize. However, with the bagging of features and training data, this problem of over-fitting is solved in the random forest algorithm, which can provide a robust prediction model. The results obtained with random forest regression show better prediction accuracy than the previously discussed algorithms.

1.11.2.2.2 XGBoost: eXtreme Gradient Boosting

XGBoost is one of the very powerful and popular machine learning algorithms that provide high accuracy for large datasets due to its optimized implementation. This algorithm follows the boosting concept where weak learners (decision trees) are grown sequentially. Each subsequent tree learns based on the prediction errors of the previous tree. A higher weight is given to improving the predictions on the data points that had a higher RMSE in the previous learner. An algorithm builds a composite model from weak learners that provides robust performance. The algorithm is designed to optimize performance at higher execution speed. The model itself is optimized with a gradient descent algorithm; this provides higher accuracy.

1.11.2.3 Artificial Neural Network

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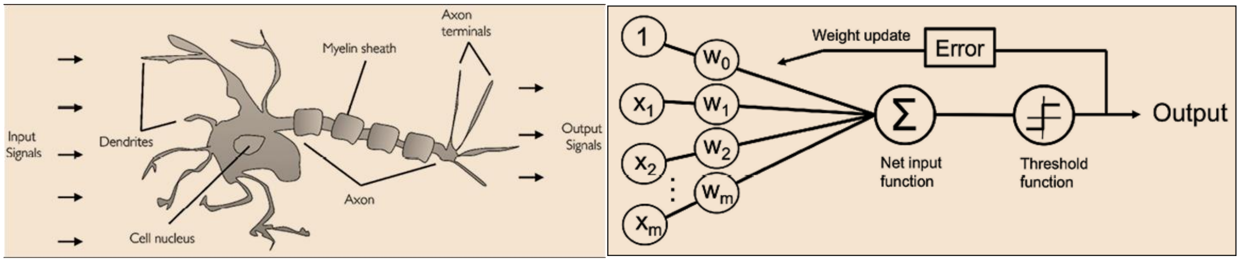

Figure 1. 9-10 showing comparison between Natural neuron(left) in a brain and artificial neuron(right)

Artificial neural networks are based on the principle of decision-making ability of neurons in the human brain. They are the building blocks of more sophisticated deep learning networks. The architecture of a neural network consists of an input layer, one or more hidden layers, and an output layer. Each layer consists of neurons where the computations take place.

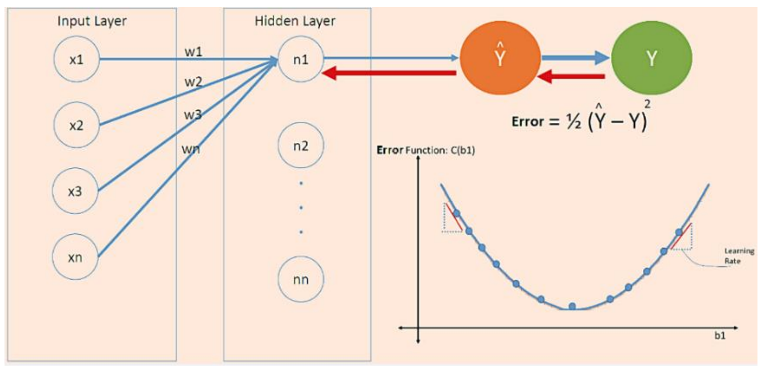

Figure 1. 11 showing how backpropagation in ANN works

A multilayer perceptron model (ANN) is created using the principle of backpropagation of errors as the primary learning mechanism.
During backpropagation of errors, the estimated errors in the model prediction are backpropagated to adjust the neural network model parameters, and updated model parameters are calculated. This iterative training process continues until a specified model accuracy or training duration condition is met.

1.11.2.4 Hyperparameter tuning review

Hyperparameters tuning consists of trying different combinations of hyperparameter and evaluating model performance.
If models are simple (i.e., linear models, tree based algorithms) the following methods are used:

- Grid Search
- Random Search

If models are complex (i.e., Neural Networks) the previous methods cannot be used for the following:

1) Training the model is very costly (time and money).
2) Trying all possible combinations is not an option

Thus, Sequential search technique can be used. It selects smartly which hyperparameters to evaluate. While Grid Search and Random Search generate all the candidate points up front and evaluate them in parallel. So, sequential search techniques pick a few hyperparameter settings, evaluate their quality, then decide where to sample next. It consists of:

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a) Iterative and sequential process

b) Not parallelizable

So the goal is to make fewer evaluations, only of those most promising candidate hyperparameters. In a conclusion, sequential search techniques pick a few hyperparameter settings, evaluate their quality, then decide where to sample next. The trade-off is less ML model training time ×time to estimate where to sample next. Moreover, sequential search makes sense when the evaluation procedure (training the model –performance) takes much longer than the process of evaluating where to sample next. Thus, bayesian optimization is a sequential strategy for global optimization of black-box functions, which does not assume any functional forms. Bayesian optimization is usually employed to optimize expensive-to-evaluate functions.

1.11.3 Bayesian Network

1.11.3.1 Background

Causal relationship

It is defined as if there is a tendency that "the larger the variable X, the larger the variable Y", it is said that **there** is **a causal relationship from** the **variable X to the variable Y.** [1.22]

Causal reasoning:

We all learn that "correlation ≠ causation", but what does that really mean correlation allows prediction, but causation is necessary for manipulation. As humans, we have a natural inclination to find causal relationships between events we observe in the world around us, even if they don't actually exist. The goal of causal reasoning is to unambiguously identify true causal effects in the domain that interests us. [1.26] Such spurious **correlations** are called spurious correlations, and variables that produce spurious correlations are called **confounding factors**. Variables that are spurious **are not said to have a causal relationship**. However, if you calculate the correlation coefficient, it will be a fairly large positive value, so there **is a correlation**.

Here, the terms are summarized as the following:

- Correlated: **When the value of variable X is large, variable Y also tends to be large.**
- There is a causal relationship: The **larger the value of variable X, the larger the variable Y tends to be.**
- Spurious: Variables X and Y are correlated but not causal

The causal relationship, increasing the X **if** Y is also increased, will be the point place called. In addition, since the absolute value of the correlation coefficient takes a large value in any relationship, it is not possible to distinguish between them by the correlation coefficient alone. [1.27]

A formal definition

We say that events A and B are "associated" if they are not independent-that is, P(A, B) ≠ P(A)P(B). We say that event A causes event B if the manipulation of A changes the probability distribution of B (although direct manipulation may actually be impossible). Moreover, causal relationships are inherently probabilistic. In addition, causal relationships respect the flow of time, even if time is not explicitly represented in the model

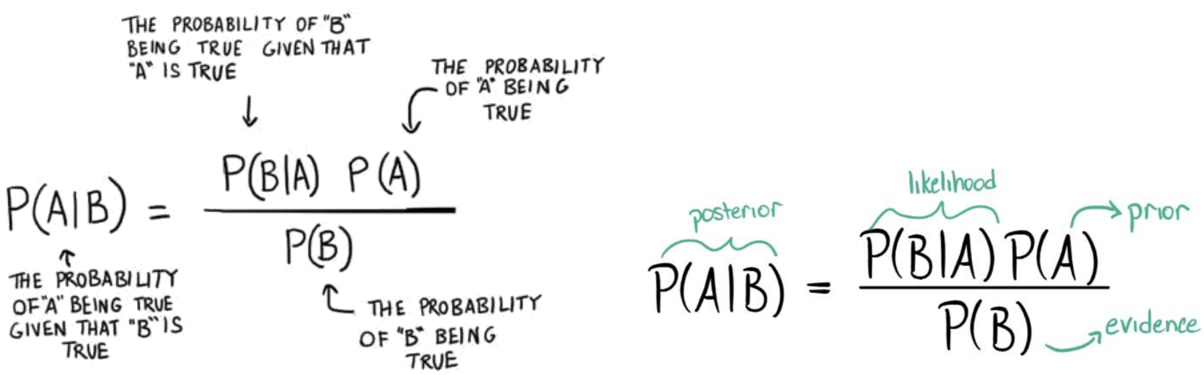
1.11.3.2 Bayesian causal networks

So far, we have used Bayesian networks to give us distribution of weights over the data provided

Bayesian networks **represent graph structures between variables based on conditional probabilities**. A Bayesian network or causal network is an expert system that captures all existing knowledge; A Bayesian network consists of

- a directed acyclic graph (a set of nodes and directed edges connecting nodes) or DAG
- A set of conditional probability tables (for discrete data) or probability density functions (for continuous data)

Bayesian networks can be used to predict outcomes or diagnose causal effects (if structures are known). Also, Bayesian networks can be used to discover causal relationships (if structures are not known). It is based on the following formula:



(Eq. 1.1)

In a causal Bayesian network, the edges are always oriented to point from cause to effect. The same semantics of independence applies in the form of the "causal Markov assumption". In many ways, causal Bayesian networks are easier to interpret than associative networks. There are several ways to calculate the dependency (arrow) in the Bayesian network. The method discussed here will be called PC algorithm. The idea with Bayesian network first is to test for (conditional) independence between each pair of variables, using all possible conditioning sets. If two variables cannot be made conditionally independent, then we put an edge between them. Moreover, the edges are then aligned using rules derived from Bayesian network semantics and d-separation

Steps followed in the algorithm: First, identify the skeleton (dependency without direction) start with a fully connected undirected graph) as shown below. Then, remove all edges (features) that are directly independent which is normally done using Pearson Chi-square test (Categorial variables), F1 test (continuous variables) or log-likelihood ratio [1.23].

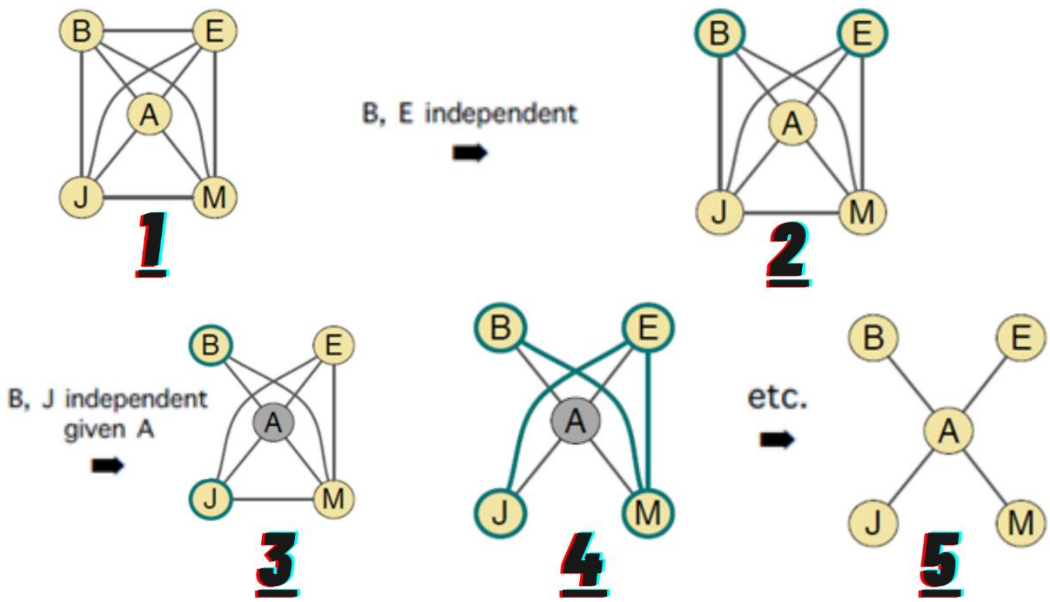


Figure 1. 12 showing the cycle of Bayesian network for DAG (graph) forming

Also, the structure learning could be constrained based, score based or hybrid based. In this master we will use constraint-based method for structure forming and a score-based method for orienting. Noting that different rules are used for orienting edges such as:

- Orientation rules
- Bayesian Information Criterion (BIC)

For the orientation rules:

Steps involved summary:

Different rules were proposed. These rules can be summarized as per the figure below. [1.24]

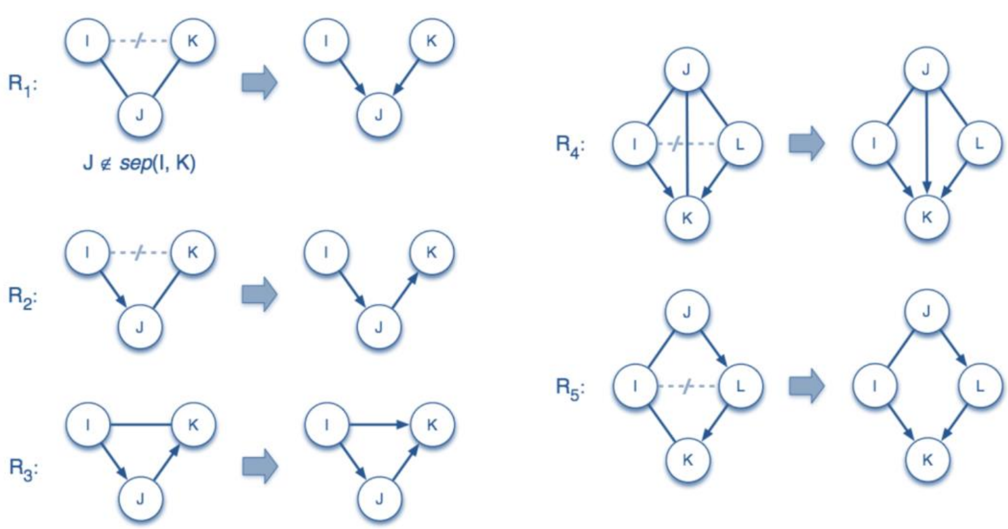
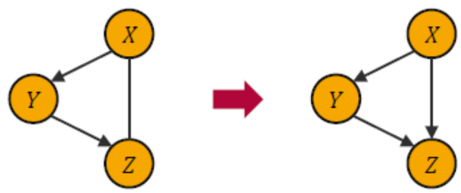


Figure 1. 13 showing all the different orientation rules

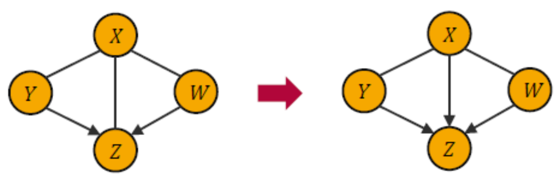
So as a summary, if the edges are not oriented and a node J separates 2 different nodes (which are independent). Thus, rule 1 is applied. Moreover, after we have oriented nodes, the other rules are applied depending of their dependency, d-separated or not and the different nodes attached to as shown in the figure 1.13. Another explanation can be as per the following:

1) there is an arrow $X \rightarrow Y$ such that X and Z are nonadjacent (Otherwise we get a new v-structure)

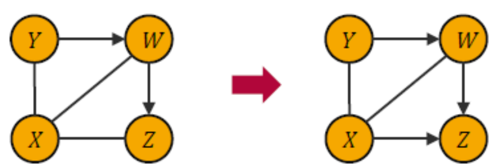
2) Orient X $- Z$ to X $\rightarrow$ Z whenever there is a chain $X \rightarrow Y \rightarrow Z$ (Otherwise we get a cycle)



3) Orient X $- Z$ to X $\rightarrow$ Z whenever there are two chains $X - Y \rightarrow Z$ and $X - W \rightarrow Z$ such that Y and W are nonadjacent (Could not be completed without creating a cycle or a new v-structure)



4) Orient X $- Z$ to X $\rightarrow$ Z whenever there are two chains $X - Y \rightarrow W$ and Y $\rightarrow W \rightarrow Z$ such that Y and Z are nonadjacent (Could not be completed without creating a cycle or a new v-structure)



Another way could be used using score-based approach in order to get the structure and orientation, here we use the score-based approach in order to get the orientation. In addition, in order to select the most appropriate structure (model) a method called Bayesian information criterion which is a type of a score based approach is used which is derived from Laplace theorem. BIC tries to minimize the score of function below or in another word to maximize the likelihood:

$$\mathrm{BIC} = -2 \cdot \ln(L) + k \ln(n) \quad \text{(Eq. 1.2)}$$

- where n is the likelihood function ,L is the size of the sample or the number of observations, K is the population parameter or the number of independent variables.
- So by running different orientations, the lowest score of a model determines the orientations of graph edges.[1.25]

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1.11.4 Reinforcement learning

1.11.4.1 Background and achievements

2016 witnessed the power of reinforcement learning to minimize Google's cost through reducing the cooling bills of Google Data Centre by 40% using DeepMind AI which is their Deep Q-Learning model. In turns it reduces CO_2 emissions [1.28] Also, RL techniques are used nowadays for applications such as:

- Self-driving cars industry automation and robotics manipulation where learning-based **robots** are used to perform various tasks also perform tasks that would be dangerous for people. While robots are trained to grasp various objects.
- Trading and finance where a RL agent can decide on such a task; whether to hold, buy, or sell.
- In natural language processing which can be used in **text summarization**, **question answering,** and **machine translation**
- In healthcare where patients can **receive treatment** from policies learned from RL systems
- Decision making for engineering tasks optimization in news recommendation in gaming in real-time bidding [1.29]

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Figure 1. 14 showing the cycle of reinforcement learning with data input

The development of RL is based on Markov Decision Processes (MDP). Thus MDP is used in the stochastic situation for decision-making where each of every event depends only on the state attained in the previous event. Which are defined as mathematical models. It states that in an environment what happens in the future doesn't depend on the past. Till 1957, when Bellman (Bellman, 1957) suggested a recursive formula optimizing the sum of all rewards along a MDP consisting of:

- State (s)
- Action (a)

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- Reward (R)
- Discount factor (gamma)

$$V(s) = max_a R(s,a) + \gamma V(s'))$$ (Eq. 1.3)

When Bellman’s equation is solved, it means that we try to find the optimal policy.
However, that equation was not analytically possible to solve until Watkins proposed the Q-learning algorithm (Watkins, 1995). Since it involves the maximization of a function, which cannot be derivative. The exploration-exploitation dilemma was solved through the use of that formula where the AI agent maximizing rewards and not to be trapped in local optimal by spending the optimal time exploring the solutions.

$$NewQ(s,a) = Q(s,a) + \alpha[R(s,a) + \gamma\, max\, Q'(s',a') - Q(s,a)]$$ (Eq. 1.4)

RL differentiates from supervised and unsupervised learning through the presence of an environment and the agent (which is the AI algorithm that learns how to succeed and operates in its environment).
The agent learns through iterative feedback loop. So it first takes an action, the state will change and based on reward it is either win or lose. The goal is to maximize the cumulative expected reward.[1.30][1.31][1.32]

1.11.4.2 Deep Q-learning

Deep Q-Learning consists of combining Q-Learning to an Artificial Neural Network. Inputs are encoded vectors, each one defining a state of the environment. These inputs go into an Artificial Neural Network, where the output is the action to play. More precisely, let’s say the game has n possible actions, the output layer of the neural network is comprised of n output neurons, each one corresponding to the Q-values of each action played in the current state. Then the action played is the one associated with the output neuron that has the highest Q-value (argmax), or the one returned by the softmax method. In our case we will use argmax. And since Q-values are real numbers, that makes our neural network an ANN for Regression. Hence, in each state st: the prediction is the Q-value Q(st; at) where at is chosen by argmax or softmax the target is:

$$r_t + \gamma \max_a (Q(s_{t+1}, a))$$ (Eq. 1.5)

the loss error between the prediction and the target is the squared of the Temporal Difference:

$$\text{Loss} = \frac{1}{2}\left(r_t + \gamma \max_a (Q(s_{t+1}, a)) - Q(s_t, a_t)\right)^2 = \frac{1}{2} TD_t(s_t, a_t)^2$$ (Eq. 1.6)

Then this loss error is backpropagated into the network, and the weights are updated according to how much they contributed to the error.

`

To conclude, in this chapter we covered the concept, history and trends of digitization in the upstream oil and gas industry with some literature about the algorithm used in the following case studies. In the next chapters we will discuss various case studies that can be used in the digitization of the industry but before that we will cover some literature as fundamentals in reservoir and production engineering then another literature regarding electrical submersible pumps will be covered (since they will be used in two of our case studies).

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Chapter 2

2 Reservoir and production engineering concepts

The performance of a well depends on a variety of variables such as pressure, formation properties, and fluid properties. And these are in turn interdependent.
In this chapter, various models for well inflow behavior and vertical lift performance are described, but first a brief explanation of the various drive mechanisms from the reservoir is given.

2.1 Drive mechanisms

Drive mechanism could be divided into natural, secondary and tertiary oil recovery.

1) According to Dake natural drive types for oil production [2.5] are the following:

- Water Aquifer drive
A drop in reservoir pressure caused by the pumping of fluids causes water in the aquifer to expand and flow into the reservoir. 50% of oil production can be caused by natural water drive

- Solution gas drive:
When reservoir pressure drops below bubble point pressure, solution gas dissolved in the oil appears as a free phase. When the pressure drops further, the highly compressible gas expands and displaces the oil from the porous medium.

- Gas cap drive:
The high compressibility of the gas and the expanded size of the gas cap ensure long lasting and efficient field performance. Up to 35% of the original oil can be recovered with a gas cap drive.

- Compression drive
This drive mechanism can occur during depletion when the aggregate is stressed beyond its elastic limit. It results in re-compaction of partially deformed or even destroyed aggregates, which can lead to a gradual or abrupt reduction in the pore volume of the reservoir.

2) **Secondary and tertiary oil recovery methods** are often used to achieve better field performance. Gas lift and downhole pumping are examples of advanced recovery techniques (Enhanced Oil Recovery, EOR).

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2.2 Inflow performance

The Inflow Performance Relationship (IPR) describes the pressure drop as a function of the production rate, where the pressure drop is defined as the difference between static and flowing well pressure (FBHP).
The simplest approach to describe the inflow performance of oil wells is to use the concept of productivity index (PI). It was developed under the following assumptions:

- The flow is radial around the wellbore
- A single phase fluid is flowing
- The permeability distribution in the formation is homogeneous
- The formation is completely saturated with the given fluid.

Flow through a porous medium is given by the Darcy equation:

$$\frac{q}{A} = \frac{k}{\mu}\frac{dp}{dl} \qquad \text{(Eq. 2.1)}$$

Using the above assumptions, it can be written as.

$$q = \frac{0{,}00708kh}{\mu B \ln\left(\frac{r_e}{r_w}\right)}\left(p_R - p_{wf}\right) \qquad \text{(Eq. 2.2)}$$

Where: q = liquid rate, STB/d
k = effective permeability, mD
h = pay thickness, ft
μ = liquid viscosity, cP
B = liquid volume factor, bbl/STB
re = drainage radius of well, ft
rw = radius of wellbore, ft
pR = average reservoir pressure
pwf = flowing bottomhole pressure

Most of the parameters on the right-hand side are constant, which allows them to be combined into a single coefficient called PI:

$$q = PI\left(p_R - p_{wf}\right) \qquad \text{(Eq. 2.3)}$$

or equivalent to:

$$PI = \frac{q}{\left(p_R - p_{wf}\right)} \qquad \text{(Eq. 2.4)}$$

This equation states that the fluid inflow into a well is directly proportional to the pressure drawdown. It is represented as a straight line on a pressure-to-rate diagram.

`

The application of the PI concept is quite simple. If the average reservoir pressure and PI are known, application of Equation 2.3 yields the flow rate for each FBHP. The PI of the well can either be calculated from the reservoir parameters or measured by measuring the flow rates at different FBHPs.
This works well for a single-phase flow, but when pumping a multiphase reservoir, the curve is not plotted as a straight line.
As the oil approaches the wellbore and the pressure drops below the bubble point, gas comes out of solution. This causes the free gas saturation near the oil to steadily increase, which means that the relative permeability to gas steadily increases at the expense of the relative permeability to oil. The greater the drawdown, the greater this effect would be. Since PI depends on the effective oil permeability, it is expected to decrease (Eq. 2.2).

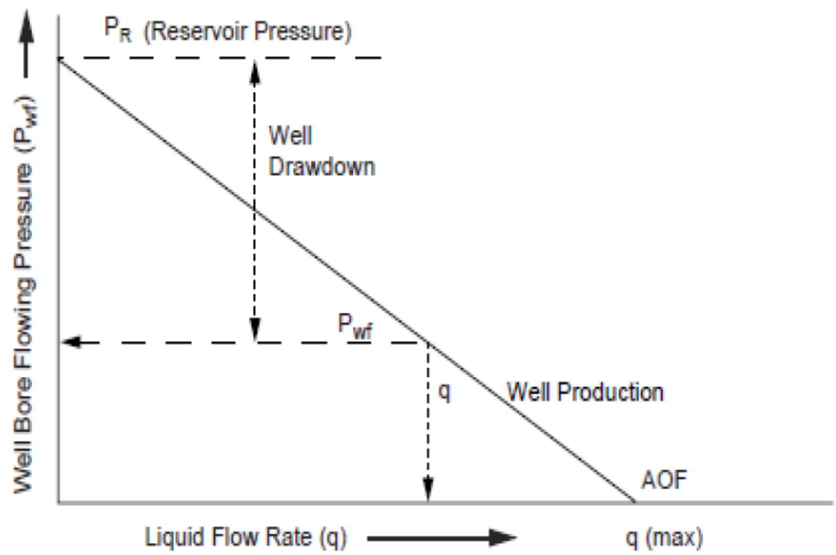

Figure 2. 1: showing IPR curve of a well

2.3 Factors affecting PI

1. Phase behavior
   - -Bubble point pressure
   - -dew point pressure
2. Relative permeability behavior
   - -Ratio of effective permeability to a given fluid (oil, gas or water) to absolute permeability of rock
3. Oil viscosity.
   - -Viscosity decreases with decrease of pressure on Pb
   - -Viscosity increases as gas comes out of solution
4. Oil formation volume factor (Bo).
   - -When the pressure decreases, the liquid expands
   - -When gas comes out of solution, oil shrinks

2.4 Multiphase flow:

Oil wells normally produce a mixture of fluids and gases to the surface, with phase conditions usually changing along the way. At higher pressures, especially at the bottom of the well, the flow may be single-phase. However, as the wellbore height increases, the continuous pressure drop causes dissolved gas to gradually escape from the flowing fluid, resulting in multiphase flow. Gas injection into a wellbore is also an example of multiphase flow.
In single-phase flow, we distinguish between laminar and turbulent flow. In two-phase flow, we additionally distinguish between flow regimes that are characteristic of the temporal and spatial distribution of the gas and liquid flow.

Many correlation were used in order to draw IPR one of them is vogel which represent ratio of pressure (Pwf/Pr) vs. ratio of flow rates (q/qmax).
Vogel used a numerical reservoir simulator to study the inflow from wells that deplete solution gas drive reservoirs. He considered cases below the bubble point and varied parameters such as discharge rates, fluid and rock properties. Vogel found that the calculated IPR curves had the same general shape given by the dimensionless equation:

$$\frac{q}{q_{max}} = 1 - 0,2\frac{P_{wf}}{2} - 0,8\left(\frac{P_{wf}}{P_R}\right)^2 \qquad \text{(Eq. 2.4)}$$

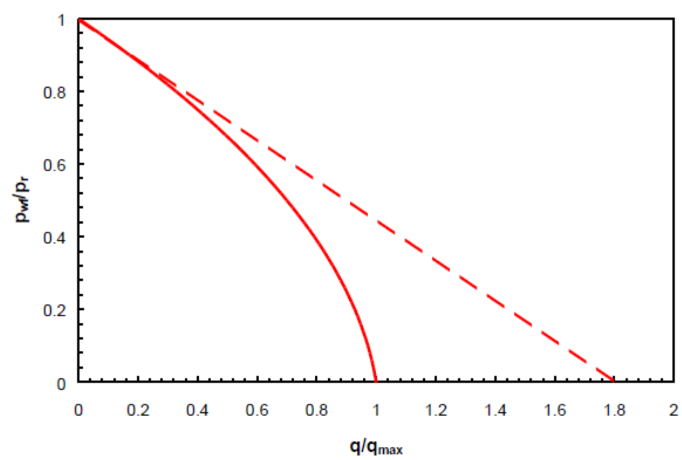

Figure 2. 2: showing IPR curve following Vogel equation

The equation is generally accepted for other driving mechanisms and gives reliable results for almost all wells with wellbore pressure below the bubble point of the oil.
There are a number of other models developed for special cases, e.g. horizontal wells, unsteady flow, fractured wells, non-darcy pressure drop, high rates, etc.

In addition, another empirical correlation is Fetkovich equation or known as normalized backpressure equation, it is an alternative to Vogel's equation.

q / qmax = [1 - (Pwf / Pr)^2]^n (Eq. 2.5)

The lower the value of n ,the greater the degree of turbulence

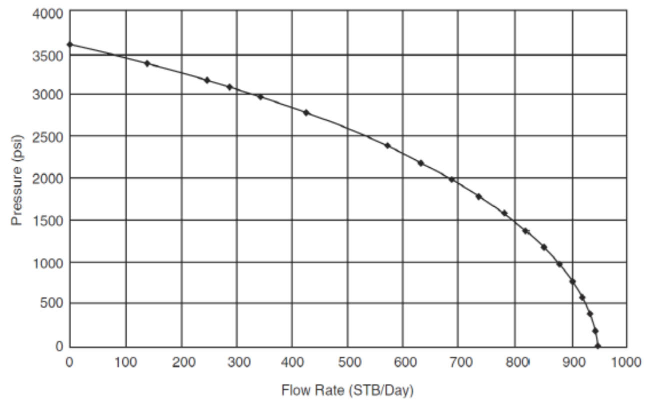

Figure 2. 3 : showing IPR curve following Fetkovich equation

A combination between Darcy and Vogel leads to the following graph:

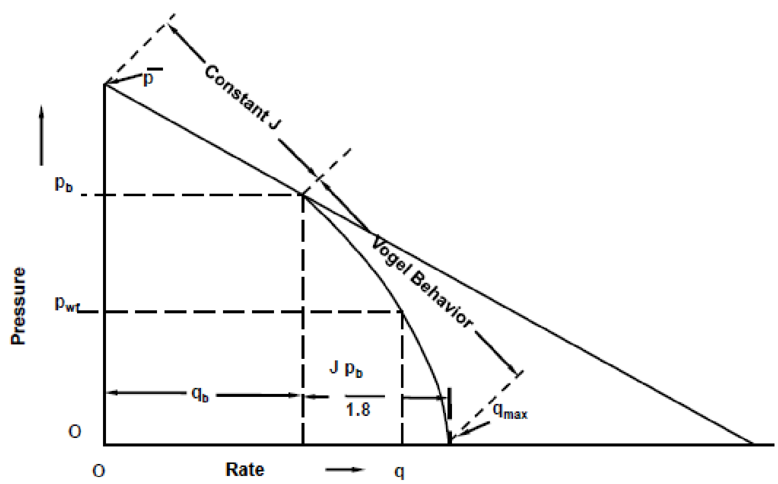

Figure 2. 4: showing IPR curve combining both regimes single and multiphase flow using Vogel for multiphase flow

So for:

- $q \leq q_b$, Darcy's law is applied where

$$q = J(\overline{p} - p_{wf}) \qquad \text{(Eq. 2.6)}$$

- $q \leq q_b$,

$$q = q_b + (q_{max} - q_b)\left[1 - 0.2\frac{p_{wf}}{p_b} - 0.8\left(\frac{p_{wf}}{p_b}\right)^2\right] \qquad \text{(Eq. 2.7)}$$

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While qmax is computed as follow:

$$q_{max} = q_b + \frac{J\, p_b}{1.8} \qquad \text{(Eq. 2.8)}$$

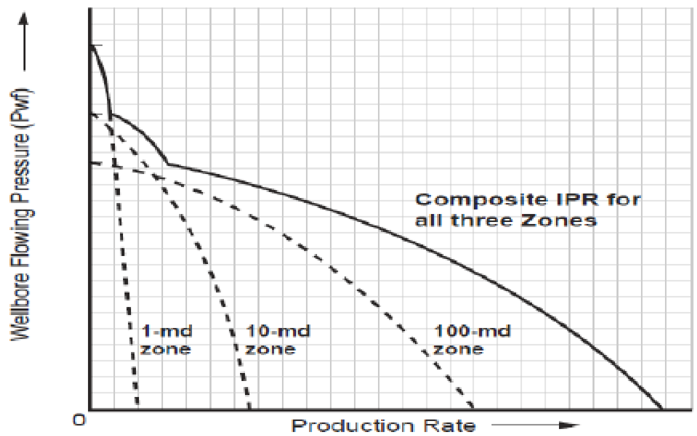

Figure 2. 5: showing IPR curves for heterogeneous formations.

2.5 Outflow

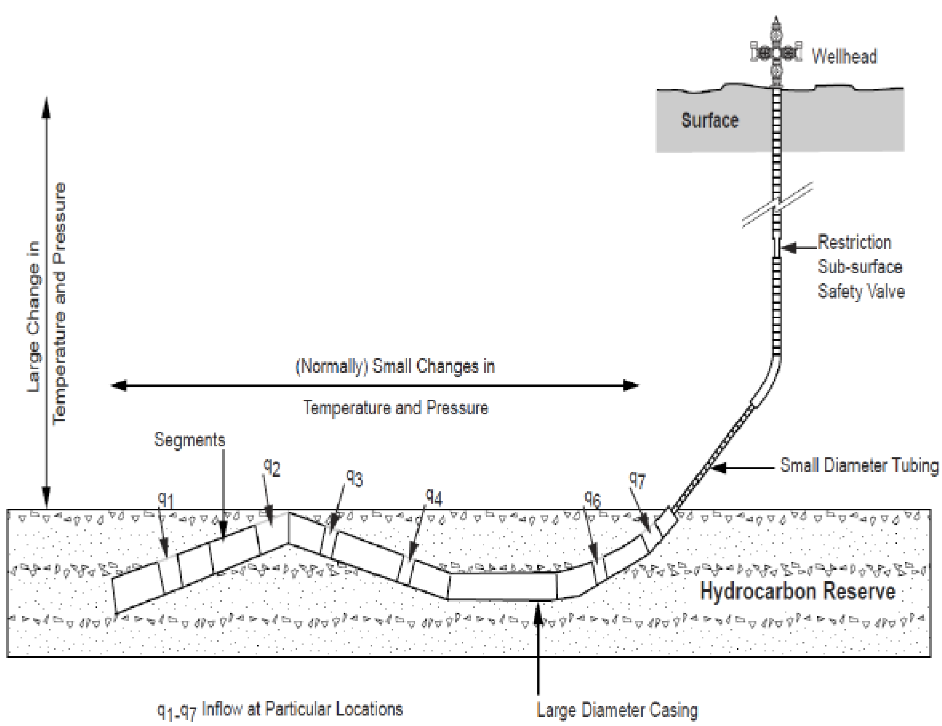

Figure 2. 6: showing fluid trajectory from reservoir to surface.

A- Vertical multiphase flow objectives include:

i- listing the three different pressure losses in a multiphase flow in a vertical well.

ii- Finding liquid holdup

iii- Calculating critical rate in order to produce liquids

$$\frac{dP}{dZ}_{tot} = \underbrace{\frac{g}{g_c}\rho_m \sin\theta}_{\text{Elevation}} + \underbrace{\frac{f_m \rho_m v_m^2}{2 g_c d}}_{\text{Friction}} + \underbrace{\frac{\rho_m v_m}{g_c}\frac{dv_m}{dZ}}_{\text{Acceleration}} \qquad \text{(Eq. 2.9)}$$

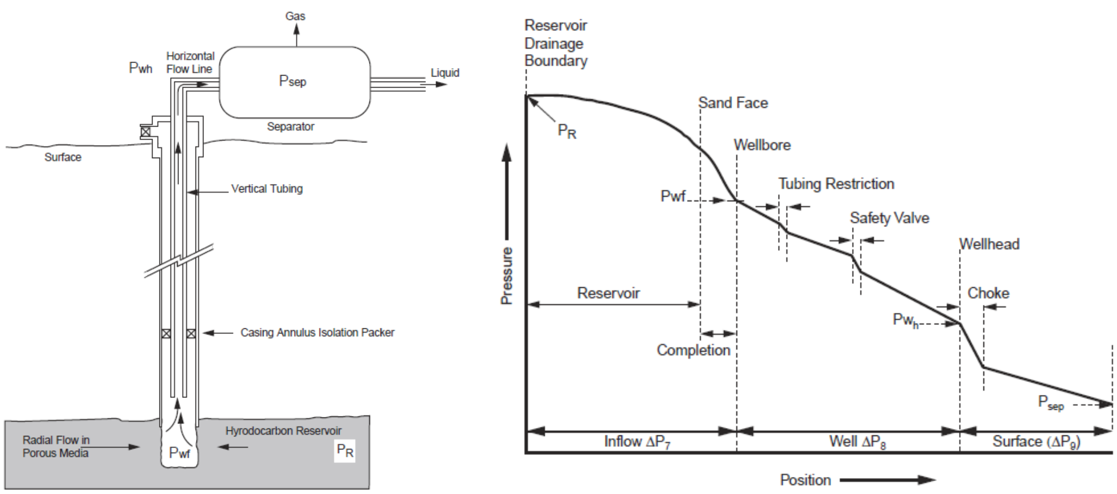

Figure 2. 7 -8 showing the fluid path in a well (to the left), and how pressure decreases within the well as it moves to surface(right).

Wellbore discharge performance, or Vertical Lift Performance (VLP), describes the wellbore pressure as a function of flow rates. According to Golan and Whitson [2.3] the discharge capacity depends on several factors;

- fluid rate,
- fluid type (gas-liquid ratio, water cut),
- fluid properties

- pipe size.

Gabor divides the total pressure drop in a well into a hydrostatic component, a friction component and an acceleration component:[2.4]

In most oilfield applications (i.e., large height difference between inlet and outlet for existing fluids), the gravity component typically accounts for about 90% of the total pressure loss. The hydrostatic component represents the change in potential energy due to the gravitational force acting on the mixture

$$\left(\frac{dp}{dl}\right)_h = \rho g \sin\beta \qquad \text{(Eq. 2.10)}$$

Where: ρ = density of fluid
β = pipe inclination angle, measured from horizontal
g = gravity constant

The friction component represents the irreversible pressure losses that occur in the pipe due to fluid friction against the inner wall of the pipe, it is controlled by fluid viscosity and geometric factors such as pipe diameter and pipe roughness.

$$\left(\frac{dp}{dl}\right)_f = \frac{1}{d} f \frac{1}{2} \rho v^2 \qquad \text{(Eq. 2.11)}$$

The type of flow is determined from the Reynolds number

$$\mathrm{Re} = \frac{\rho v d}{\mu} \qquad \text{(Eq. 2.12)}$$

The boundaries between flow regimes are:
Re $\leq$ 2000: Laminar flow 2000 Re $\leq$ 4000: Transition between laminar and turbulent flow 4000 Re: Turbulent flow.

For laminar flow, f = 64/Re (Moody friction factor). However, for turbulent flow, the determination of the friction factor is more complicated and there are several ways to calculate the friction factor.
The acceleration component represents the changes in kinetic energy of the flowing mixture and is proportional to the changes in flow velocity. The term is often negligible, except in systems with fluid expansion.

$$\left(\frac{dp}{dl}\right)_a = -\rho v \frac{dv}{dl} \qquad \text{(Eq. 2.13)}$$

Therefore, the total pressure loss function is not particularly sensitive to the value of the friction loss coefficient.

2.6 Other effects

1) **Influence of fluid flow rate on pressure drop**
From the friction equation, it is clear that friction losses increase as the fluid flow rate increases (v increases). The hydrostatic gradient also increases as the fluid flow rate increases.

2) **Effect of gas-liquid ratio on pressure drop**
An increase in the gas-liquid ratio (GLR) leads to a reduction in the hydrostatic gradient. On the other hand, an increased GLR increases the frictional forces and has an opposite effect on the wellbore pressure. When the contribution of friction becomes larger than that of hydrostatic forces, the actual wellbore pressure starts to increase. From a gas lift perspective, this means that there is a limit to how much gas can be advantageously injected.

3) **Effect of water cut on pressure drop**

Increased water cuts lead to increased fluid density, which in turn increases hydrostatic forces and pressure in the wellbore

4) **Effect of pipe size on pressure drop**

It can be seen from equation above that a larger pipe diameter reduces the pressure gradient due to friction. However, there is a limit to which the diameter of the casing can be increased. If the diameter is too large, the velocity of the mixture (v=q/A, A: pipe cross-section) will not be sufficient to lift the fluid, and the well will begin to fill with fluid, resulting in an increase in hydrostatic pressure.

5) **Slippage**:
-The gaseous phase moves at a higher velocity than the liquid phase, owing to buoyant forces.
-Consequence is a change in the areas of the individual phases in an element.
-The slip-corrected liquid area is referred to as LIQUID HOLDUP.
-Correction of phase volumes to holdup volumes by multiphase correlations.

6) **Liquid Hold-up:**

Since that the hydrostatic pressure in a multiphase flowrate depends on the density of the mixture. knowing that the mixture density depends on the saturation of each phase and the density of each phase. This makes hold-up important. Since we are producing oil and gas. Gas is faster than oil, so gas will be produced first. Noting that the liquid production is not continuous until it fills the whole column to be produced and this column can kill the well. First, the oil is produced by shear of gas. At interface, it creates a force and produces oil. Holdup is reducing the area for gas flow. Gas will move faster until it reaches equilibrium. If diameter of tubing or casing is big, we should expect a large hold-up of liquid because the velocity of the gas is smaller (since we have a larger diameter). So, we will keep having a high holdup until a point where the amount reached in is equal to the one produced on surface. So, to reduce hydrostatic head, we should reduce hold-up. thus, we need to increase gas velocity (by reducing pipe diameter) but reducing diameter will increase friction.

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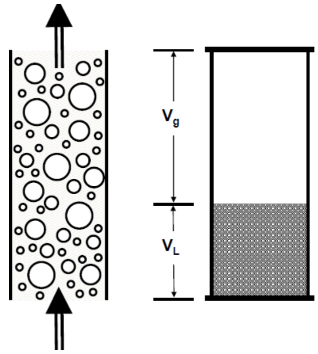

$$H_L \equiv \frac{V_L}{V_L + V_g}$$

$$\rho_m = H_L \rho_L + (1 - H_L)\rho_g$$

Figure 2. 9: showing fluid holdup, with holdup calculation formulas.

7) **Annular flow:**

Gas slip tends to be reduced in the annular ring (compared to a circular tube of the same cross-section) as the distance between the wall surfaces is reduced.

Under certain circumstances, the annular space between tubing and casing is a more efficient than the tubing itself.

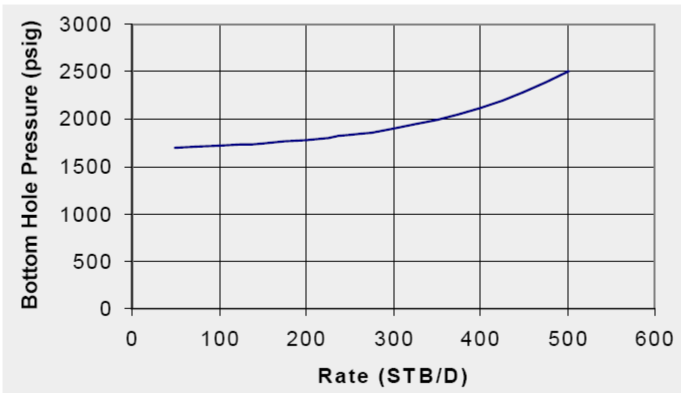

Figure 2. 10: showing the change in bottom hole pressure (Psig) vs flow rate (STB/D)

2.7 VLP

So the curve that represents the production, (production curve) is called VLP.
It is relating the change in pressure with respect to flow rate. Pressure drops are calculated as per the equation above.

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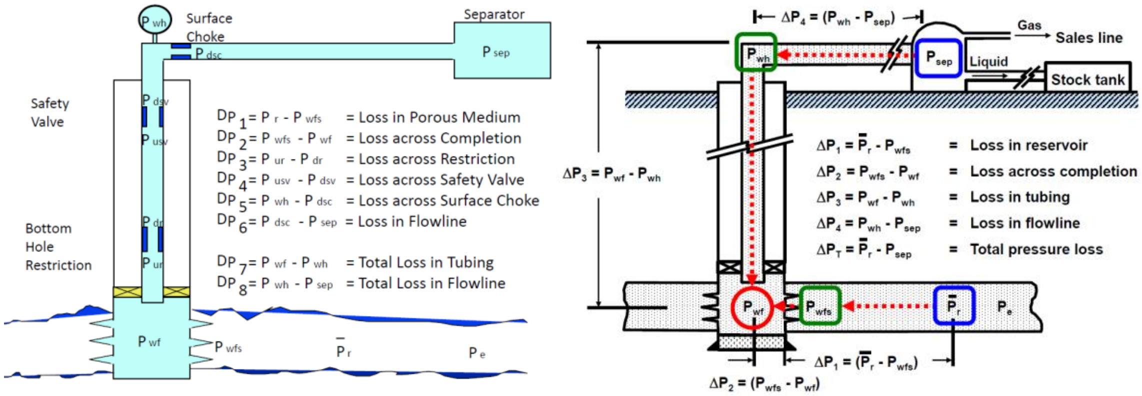

Figure 2. 11- 12: showing pressure loss across different parts from the reservoir to the separator.

Noting that VLP and IPR curves are dynamic, they keep changing with field life.

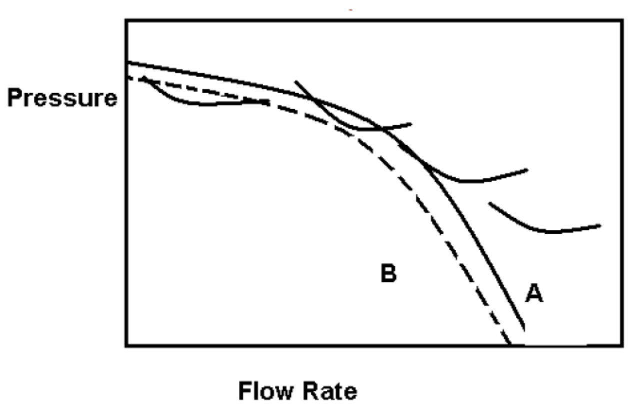

Figure 2. 13: showing IPR and VLP curves simultaneous changes..

Noting that when the VLP doesn't cross the IPR curve. Here, we need to use an artificial lift method.

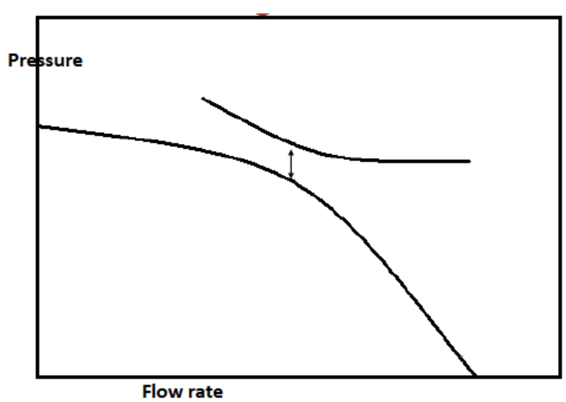

Figure 2. 14: showing when IPR and VLP curves doesn't cross, thus it needs an artificial lift method.

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2.8 Variables

2.8.1 Inflow variables:

Outflow variables are the follow:

- Depth of the reservoir (contact depth)
- Radius of the reservoir
- Differential pressure (the main driving force for the movement of fluids) (with skin included)
- Viscosity of the hydrocarbon

2.8.2 Outflow variables

Outflow variables are the follow:

- Diameter and length of the flow path (the casing below the packer and the piping)
- Velocities in each section (above the critical value for lifting liquids)
- Hydrostatic head (the flowing head and the static head as back pressure)
- Back pressures (fracture, perforation, and pipe friction; choke; surface line friction; separation and sales line pressure)

To increase flow: we need to:

- Increase pressure differential between reservoir and separator.
- Investigate and eliminate the major pressure drops.
- Maintain velocities above critical velocities in each section.

2.9 Flow regimes

In a non-depleted oil reservoir, expansion of gas occurs when the gas rises from the bottom of the well. The expanding gas can entrain and carry fluid when the flow rate reaches the critical velocity (the velocity required to lift fluid).
Noting that the volume of the gas bubble (and indirectly the velocity of the liquid flowing upward) is controlled by the pressure surrounding it. This pressure is provided by the pore pressure of the formation and controlled by the restriction and other back pressure resistances.
The nature of the flow pattern changes as the gas expands. One or more of the flow patterns may be present in different parts of the wellbore. The flow patterns can account for differences in heave, corrosion, and discharge.

The nature of the flow pattern changes as the gas expands. One or more of the flow patterns may be present in different parts of the wellbore. The flow patterns can account for differences in:

- lift,
- corrosion,

- discharge.

In the case of vertical flow, a distinction is made between the following flow regimes
- Slug flow
- Churn flow
- Dispersed bubble flow
- Annular flow

Figure illustrates the flow regimes for vertical flow. The same observations apply to vertical flow as to horizontal flow. The major difference is that no stratified flow can be achieved for vertical (simultaneously upward) flow. The equivalent flow regime at identical flow rates of gas and liquid is slug flow with very slow spherical Taylor bubbles.

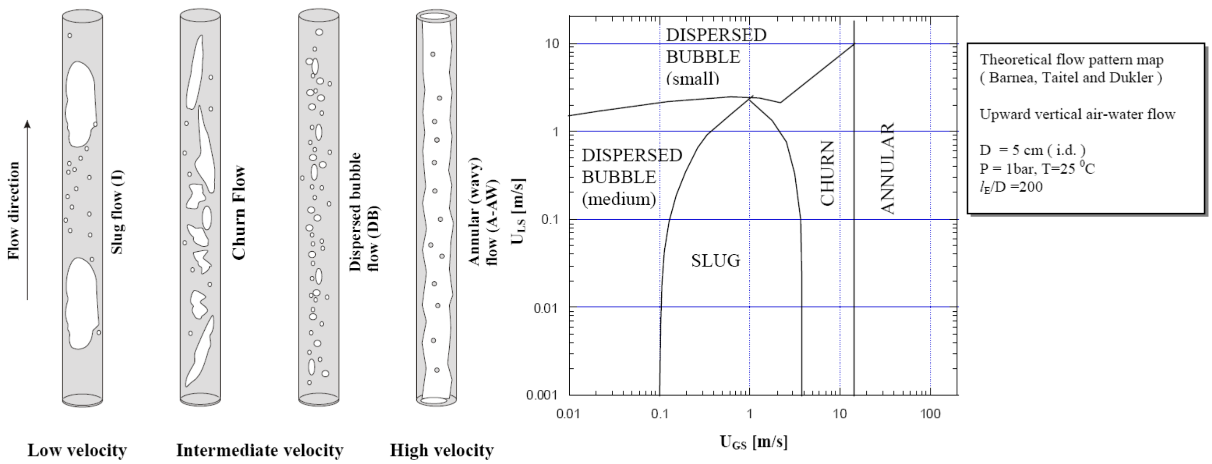


Figure 2. 15- 2. 16: showing different flow patterns in a vertical well(left), with flow pattern map of Barnea, taitel and Dukler(right)

The surface velocities are defined by:

$$U_{LS} = \frac{q_L}{A} \qquad U_{GS} = \frac{q_G}{A} \qquad \text{(Eq. 2.14-15)}$$

They are also called apparent velocities or volume flow rates. From the definition we see that the volume flows and the pipe cross section A are known, the surface velocities follow directly.
The phase velocities are the real velocities of the flowing phases. They can be defined locally (at a specific location in the pipe cross-section) or as a cross-sectional average for the pipe. They are defined by:

$$u_L = \frac{q_L}{A_L} \qquad \text{(Eq. 2.16)}$$

$$u_G = \frac{q_G}{A_G} \qquad \text{(Eq. 2.17)}$$

`

Gas and liquid generally flow at different phase velocities in the pipe flow. The relative phase velocity or slip velocity is defined by:

$$u_S = |u_G - u_L| \qquad \text{(Eq. 2.18)}$$

Thus, slip velocity has the same unit as phase velocities. In addition, the slip ratio is commonly used:

$$S = \frac{u_G}{u_L} \qquad \text{(Eq. 2.19)}$$

Note that the slip ratio is dimensionless. The slip effect occurs in inclined flow and is caused by the difference in density between the gas and the liquid, which in turn causes a difference in velocity; the gas rises through the liquid.
"Hold up" is a consequence of slip and is defined as the fraction of the tube occupied by the liquid.
Correlations for multiphase flows are used to predict the fluid hold-up and the friction pressure gradient. Common correlations consider the oil and gas together as one equivalent fluid. They are therefore more correctly referred to as 2-phase flow correlations. Depending on the particular correlation, flow regimes are identified and specific holdup and friction gradient calculations are performed for each flow regime.

Some of the most widely accepted correlations for oil wells are:

1) Duns and Ros:

- For high gas-liquid ratios and flow velocities have induced flow regime behavior this correlation is recommended.
- it is the result of laboratory work observing fluid retention and flow regime.
- determine slip velocity (and consequently fluid retention) and friction factor by using a flow pattern map.

2) Aziz, et al.:

- A new correlations was presented for bubble and slug flow.
- Using Duns & Ros for transitional and mist flow.
- with the revision of the flow regime map.

3) Hagedorn and Brown:

- using a 1500 ft. test well with 1 inch, 1.25 inch, and 1.5 inch their method was developed experimentally
- The correlation is recommended for wells with minimal flow regime effects and generally with a GLR of 10,000 scf/bbl and it is used extensively throughout the industry.

4) Orkiszewski:

- using the work of Duns & Ros and Hagedorn & Brown this correlation was developed

- Using Duns and Ros for transitional and mist flow
- It is designed to eliminate pressure discontinuities.

5) Beggs and Brill

- Experimentally developed using a 1-inch and 1.5-inch pipe tilted at various angles.
- Created to account for the inclined flow.
- The correlation is recommended for deviated wells or horizontal flow.

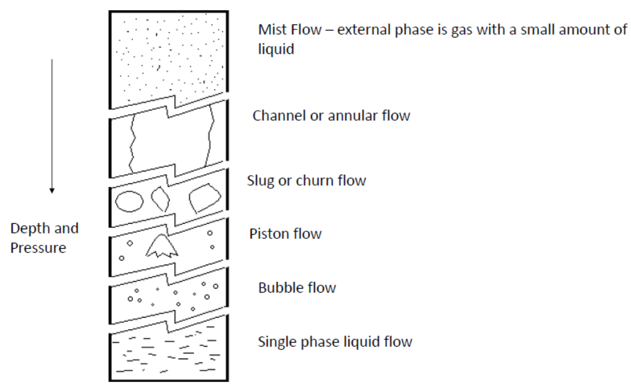
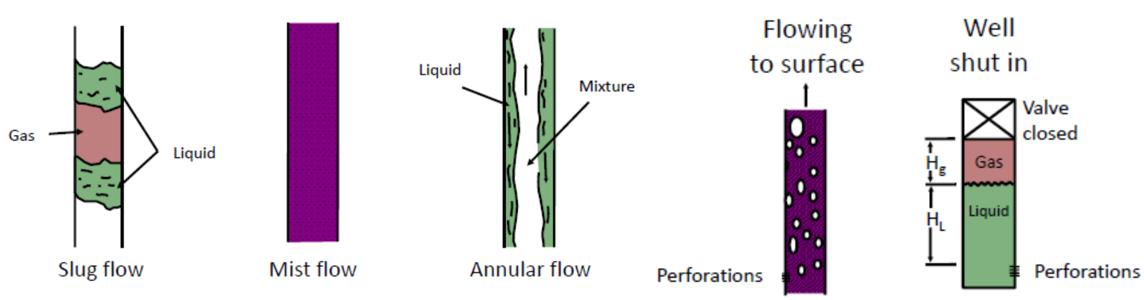


Figure 2. 17: showing different flow patterns in a vertical well

Different flow patterns depend on:

- -phases distribution
- -flow velocity
- -viscosities
- -interfacial tension



Figures 2. 18- 2. 19: showing different flow patterns in a vertical well(left), and showing phases in flowing and shut-in(hold-up liquid) oil wells(right)

2.10 Operating point

To calculate the production rate of the well, the wellbore pressure is required, which simultaneously satisfies the relationships IPR and VLP.
By plotting IPR and VLP on the same graph, the production rate can be determined.

The system can be described by an energy balance expression, simply by the principle of conservation of energy over an incremental length element of the pipe.
The energy supplied to the system by the flowing fluid must equal the energy leaving the system plus the energy exchanged between the fluid and its surroundings.

Node Analysis procedure:

- determine which components in the system can be changed.
- select a component to be optimized.
- Select the location of the node.
- Develop expressions for the inflow and outflow.
- Obtain the data necessary to calculate the components for pressure drop versus flow.
- determine the effect of changing the properties of the selected component by plotting the inflow against the outflow and reading the intercept.

Repeat the procedure for each component to be optimized.

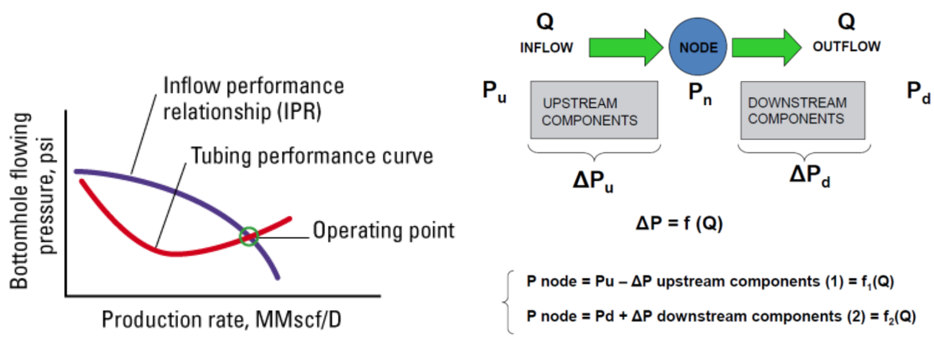


Figure 2. 20- 2. 21: showing the operating point(intersection between VLP and IPR curves)(left), and nodal analysis brief explanation(right)

2.11 Artificial lift

Maximizing the use of natural energy in a reservoir is critical for any production facility. In a naturally flowing well, enough energy is stored in the reservoir to pump the produced fluid to the surface. Reservoir pressure and formation gas provide this energy in the flowing well. When the energy of the reservoir is too low for natural flow, or when the desired production rate is greater than the energy of the reservoir can supply, it becomes necessary to artificially raise the well in some way. In 2006, according to Oilfield Review, 90% of the world's oil wells had some form of artificial lift [2.8]
An oil well usually flows naturally initially, meaning that the pressure at the bottom of the well is sufficient to overcome the pressure losses in the well and in the flow line to the separator.
When the criterion is no longer met because the pressure at the bottom of the well drops or the pressure losses in the well become too great, the natural flow ceases and the well dies.
The increased downhole pressure losses may be from increased overall density due to decreased gas production, increased water cut, or mechanical problems such as wellbore constrictions (scale, etc.).
Artificial lifting methods can be divided into two groups, those that use pumps and those that use gas.[2.9]
AL types:

- Beam Pump / Sucker Rod Pumps (Rod Lift)
- Progressive Cavity Pumps (nozzle/piston lifting)
- Subsurface Hydraulic pumps
- Electric Submersible Pumps (ESP)
- Gas lift

2.11.1 Artificial Lift Selection

In order to realize the maximum potential from the development of an oil or gas field, the most economical method of artificial lift must be selected. Here some of the most common methods of selecting an artificial lift system are discussed. In most cases, the selection criteria is what has worked best or which lift method performs best in similar oil fields. Also, the equipment and services available from vendors can easily determine which lift method is used. However, when significant well maintenance costs and high production rates are part of the scenario, it becomes prudent for the operator to consider most, if not all, of the evaluation and selection methods available. If the "best" lift method is not selected, factors such as advantage/disadvantages also by using diagrams showing the range of depth and rate in which certain types of ESPs can operate. Such diagrams are a guide to initial selection options along with advantage/disadvantage lists. Special well conditions, such as high viscosity or sand production, may result in the selection of a lift method not initially indicated on the charts. Specific designs are recommended for certain well conditions to more accurately determine the rates possible from specific depths. [2.6] Also, this selection could be based on long-term maintenance costs, delayed production during rework, and excessive energy costs (poor efficiency) can drastically reduce the net present value (NPV) of the project.
A more thorough selection technique depends on the economics of the life of the available artificial lifting methods. In turn, the economics depend on system component failure rates, fuel costs, maintenance costs, inflation rates, expected revenue from produced oil and gas, and other factors that may vary from system to system.

A typical NPV formula may be as follows:

$$NPV = \sum_{i=1}^{n} \frac{WI(Q_{HC} \times P_{HC} - Cost - Tax)_i}{(1+k)^i}$$

(Eq. 2.19)

Where: WI = Work Interest (Talisman Energy Norge has 61% on Gyda)
Q = Oil rate
P = Oil price
Cost = All costs, operational (Opex) and capital (Capex)
Tax = Governmental taxes
k = depreciation rate of the project (percent)

To use the NPV comparison method, the user has to have a good knowledge regarding the associated costs for each system. This requires the user to carefully evaluate each system for the particular well and be aware of the cons and benefits of each method and for any additional tool that may be required. Since

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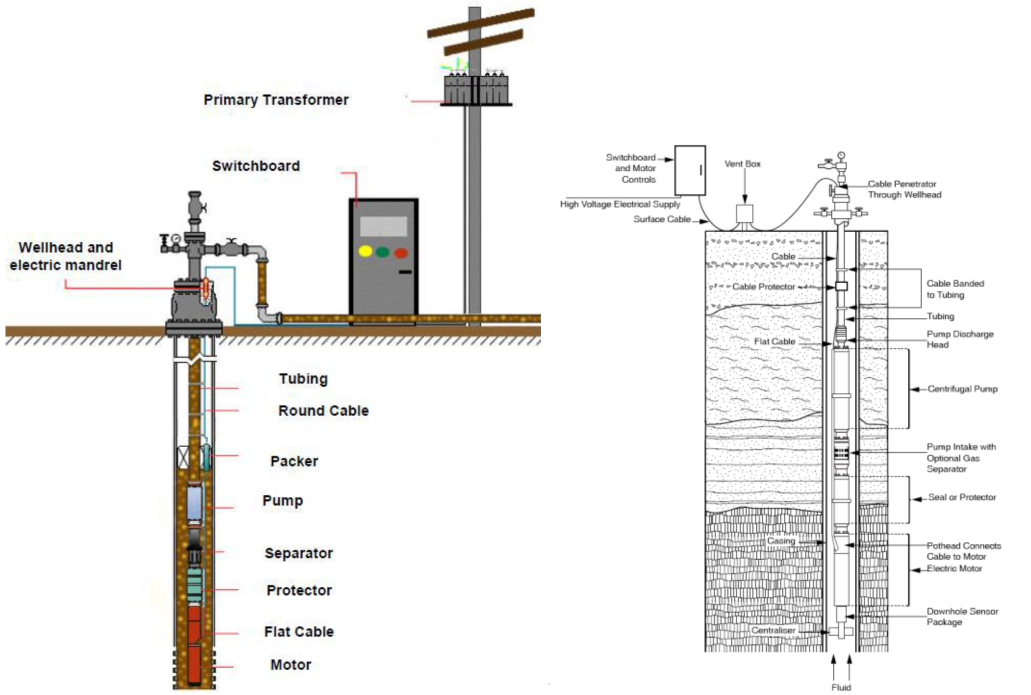
energy costs are part of the net present value analysis, a design for each feasible method must be determined prior to performing the economic analysis to better determine the efficiency of a particular system.

Chapter 3

3 Electric Submersible Pumps (ESPs)



Figures 3. 1- 3. 2: showing ESP system different components.

In the early stages of an oil field, the delta P (pressure difference) between reservoir pressure and wellhead pressure may be sufficient for the well to produce under its own energy. As time progresses, the reservoir pressure gradually decreases and eventually production can no longer be sustained naturally. Artificial lift are techniques used to artificially increase the production rate of a well. Pumping is a very common method of introducing artificial lift into the field.
Quite simply, a pump - any pump - provides the pressure needed by the well to produce a given rate of flow.

Different pumps do this in different ways:

- Centrifugal pumps - ESPs - have a unique pressure/flow profile for each stage type.
- (Sucker) Rod Pumps have a fixed flow rate for a given design (stroke, speed, plunger diameter).
- PCPs, like rod pumps, have a fixed flow rate for a given design (rotor/stator design, speed).
- Screw pumps have a fixed flow rate for a given design (screw design, speed)
- Centrifugal pumps generate a pressure that decreases as the flow rate increases
- The Electric Submersible Pump is a multistage centrifugal pump.
- Gas lift is another example of Artificial lift that is based on gas injection into the reservoir.

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Below we can find the various advantages/disadvantages of an ESP.

Electric submersible pump (ESP)	
Advantage	**disadvantage**
Can lift extremely high volumes. With high efficiency over 10,000 BPD	Can only be used with electric current.
Unobtrusive in urban areas	High voltages (1000 V) are required.
Applicable in offshore areas	Impractical in shallow boreholes with low volume.
Easy to perform corrosion and scale treatment.	Expensive modification of equipment to suit decreasing production capacity from the well.
Easy to operate.	Cable causes pipe handling problems.
Easy to install downhole pressure sensor for telemetry of pressure to surface by cable.	Gas and solids (sands,..) production are problematic.
Availability of different sizes and adaptable to boreholes with 4 1/2" pipes or large (or minimum allowable outer diameter casing)	Lack of production rate flexibility.
Crooked holes are not a problem.	More downtime when problems occur because the entire unit is downhole. Limitations of casing size
Lifting costs for large volumes generally very low makes it economical and efficient in cost per barrel.	Cannot be placed below the fluid inlet without a protective shroud to allow fluid past the motor. The shroud also allows the outside of the motor to be protected by corrosion inhibitors.
Minimal need for surface finishing	System is limited in depth due to cable cost and inability to install sufficient power downhole.
Low maintenance requirements	Not easy to analyze unless you have good technical knowledge.
Use in deviated wells and vertical wells with doglegs	Cannot run dry
vertical operating depth up to 15,000-ft	Limitation at high temperatures
small footprint in offshore application	
more than 10% gas reduces efficiency with gas handling equipment	
operates with well temperatures up to 260°C	

Table 3.1 showing advantages and disadvantages of an ESP. [2.1]

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The electric submersible pump (ESP) is a very effective artificial lifting method to pump production fluids to the surface. Nowadays, more than 130,000 ESP's are installed worldwide [2.2]. Due to its wide range of operation, electric submersible pump is the fastest growing type of artificial lifting technology. The ESP is driven by an electric motor that is also installed in the wellbore. The frequency of the ESP can be varied to change the amount of additional lift and therefore the production rate of the well.

Electric Submersible Pump systems consist of an electric motor and centrifugal downhole pump unit running on a production string and connected by a power cable to the control mechanism and transformer at the surface. In a typical application, the downhole pump is suspended from a tubing string suspended from the wellhead and is submerged in the wellbore fluid. The pump is closely connected to a submersible motor, which is powered by the power cable and surface control. The prime mover of the ESP system is a three-phase submersible motor. The motors run at a rated speed and frequency. The shaft is connected to the seal chamber section and the motor. It transmits the rotary motion from the motor to the impellers of the pump stage. The shaft and the impellers are fitted with a key, and the key transmits the torque load to the impeller. The centrifugal pump is so named because the head added to the fluid is largely due to centrifugal action
characterized by:

- Small diameter
- Large number of stages
- High design loads

3.1 Components and operating mechanics

- Underground Equipment
- Surface Equipment
- Gas separator

The ESP system can be divided into surface components and downhole components.
These components are listed below:

3.2 Surface components

- Transformers
- Motor control cabinet from Variable Speed Drive (VSD) or Soft Start
- Distribution box
- Cable Venting box
- Wellhead

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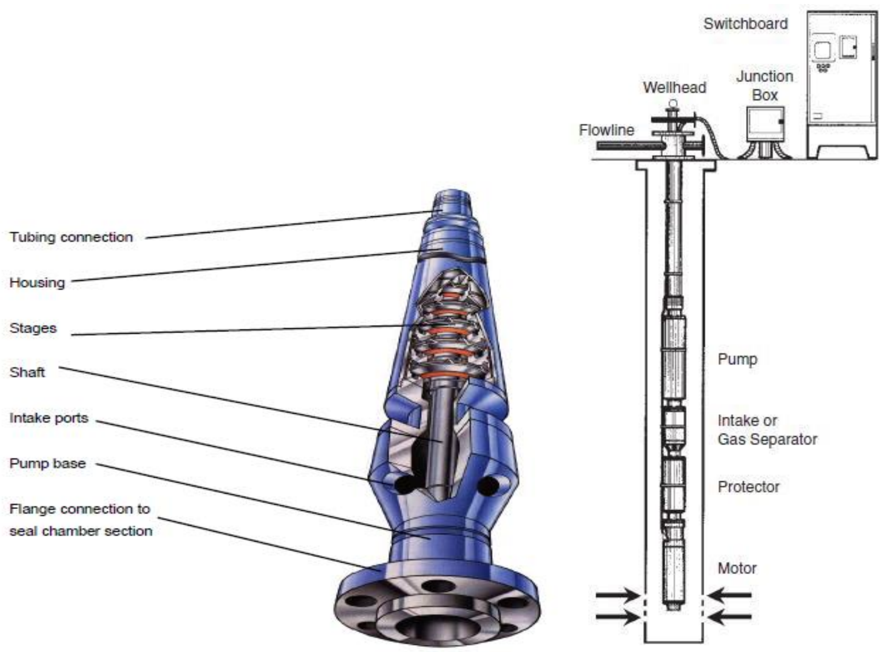
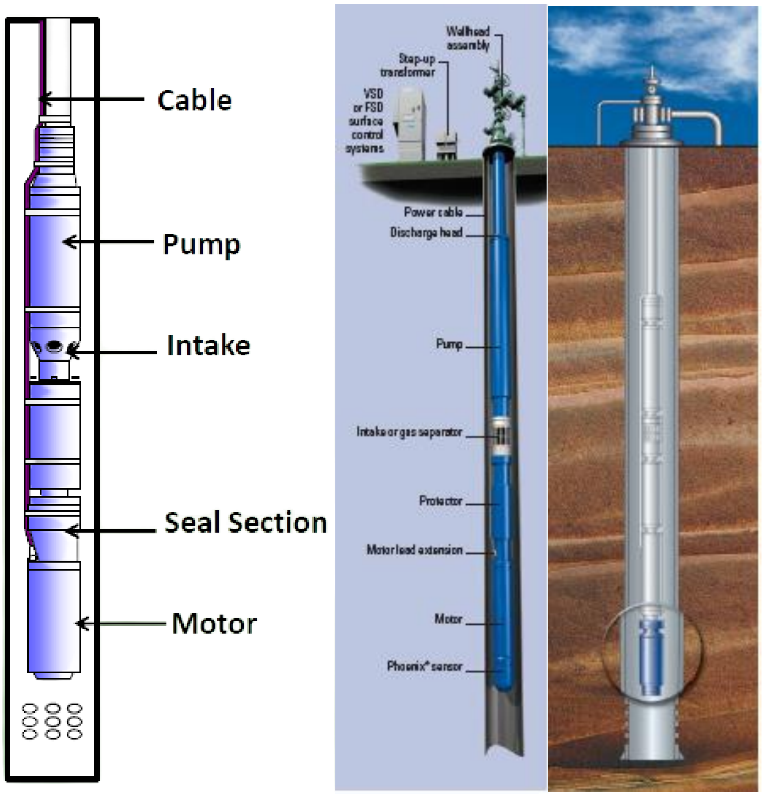
3.3 Downhole Components

- Cable
- Cable protection
- Cable clamps
- Pumps
- Gas separators
- Sealing
- Motor:
- Sensor: Data Acquisition Instrumentation
- Drain Valve
- Check valve



Figures 3. 3- 3. 4: showing ESP componets(left), other picture (right) showing ESP system components [2.2, p.52]



Figures 3. 5-6-7 showing zoomed ESP componets(left), an example of a complete ESP system picture(in the middle), for the picture to the right it shows where sensor can be mounted on the pump (below the motor) to collect data such as downhole pressure, temperature, and vibration to provide data for pump monitoring.

3.4 Concepts

The ESP is a multistage centrifugal pump. The type of stage used determines the design volume rate of liquid delivery. The number of stages determines the total head produced and the motor power required Moreover, the ESP operates in a vertical position. Each stage consists of two main parts, the impeller and the diffuser. The electric downhole motor turns the impellers via a shaft and adds kinetic energy to the pumped liquid. This kinetic energy is converted to potential energy (pressure/head) by the diffuser, which lifts the fluid from the reservoir to the surface. The stages of the pump are the components that cause a pressure rise in the fluid. A stage consists of a rotating impeller and a stationary diffuser.
The stages are connected in series to gradually increase the pressure to the value calculated for the desired flow rate. Each stage (impeller/diffuser combination) adds a certain pressure or head to the liquid. When the liquid reaches the top of the pump, it builds up enough pressure to be lifted to the surface and into the separator or flow line. The fluid flows into the eye area of the impeller and receives energy in the form of velocity as it is propelled radially outward through the impeller channel. After exiting the impeller, the fluid makes a turn and enters the diffuser channel. As it flows through this channel, the liquid diffuses, or converts velocity to pressure. This process is repeated as the liquid enters the next impeller and diffuser set. This process continues until the liquid has passed through all stages and the design pressure is reached. This pressure rise is often referred to as the total head (TDH) of the pump.

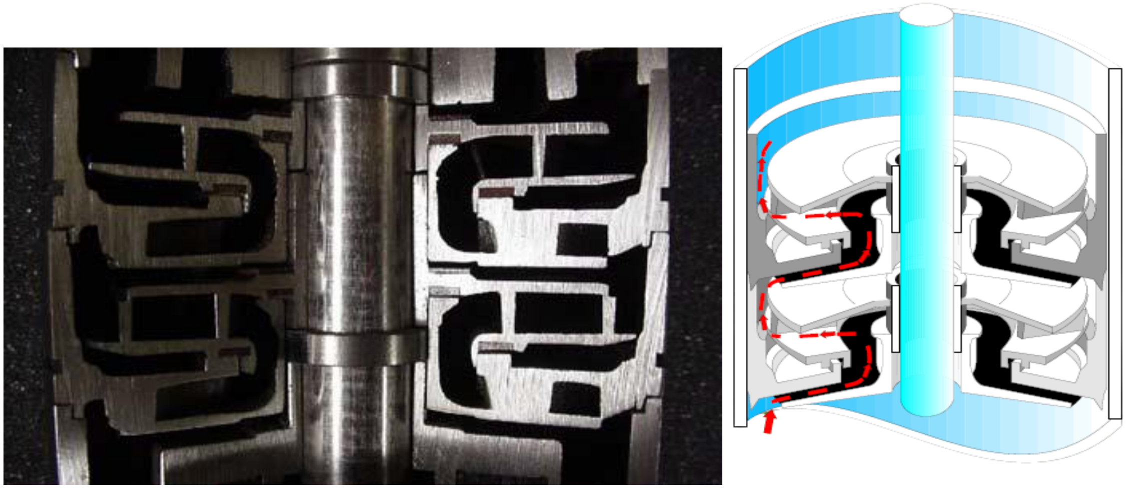


Figure 3. 8-9 showing (right) the fluid entering the impeller through the "eye" near the shaft and exits the impeller at the outer diameter (OD) Diffuser (in blue) diverts the fluid into the next impeller, other picture (left) showing a cross section view of a real ESP.

Depending on the discharge direction of the impeller, ESP's can be divided into radial, mixed and vertical flow, but only radial and mixed flow are used in industry. Radial flow provides more head, while the mixed flow configuration is better at handling gas (up to 40% at pump suction compared to 20% for radial flow) and solids in a radial stage, flow enters the impeller or diffuser parallel to the shaft axis and exits perpendicular to the shaft. Because of its flat shape, it is often referred to as a "pancake" or "mushroom" stage. The second design is the mixed flow stage, where the flow exits the impeller at an angle of less than 90° to the shaft. The mixed flow design handles greater flow velocities than the radial stage and is not as susceptible to free gas and particles.

Figure 3. 10 showing mixed flow stage 3D view

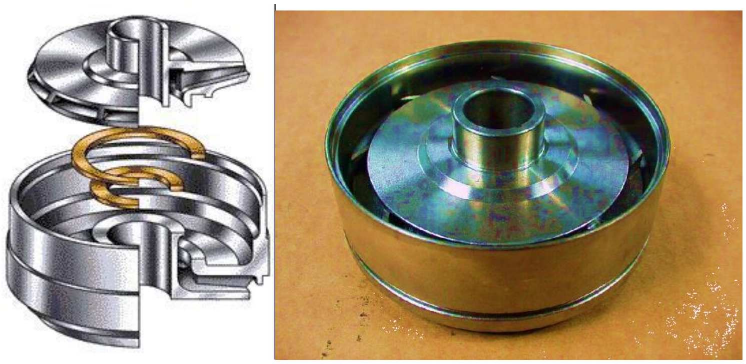


Figure 3. 11-12 showing radial flow stage 3D view(left), real picture for radial flow stage(right)

A key feature for both types of stages is the way they transmit the axial thrust generated. Typically, pumps less than 6 inches in diameter are built as "floater" stages. These allow the impellers to move axially on the pump shaft between the diffusers. They typically run in a downward thrust position and at high flow rates they can go into upward thrust.

Another important consideration is whether the impellers are fixed or floating.
In a "compression" pump: All impellers are fixed to the shaft, so when the shaft moves up or down, all impellers follow. Therefore, the shaft and the main thrust bearing (in the protector) must support the entire axial load. In a "floater" pump:

- the impellers can move inside the diffuser.
- The main axial loads are carried by the thrust washers between each stage (up and down thrust washers).
- Lower capital cost due to reduced manufacturing time, without the need to attach all impellers to the shaft, is the major advantage of floating pumps.

Compression pumps can also be used in areas with down-thrust, while floater pumps only operate in the designed operating range.

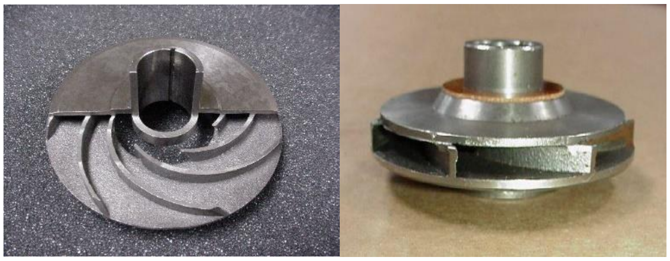


Figure 3. 13 showing sectional view of two impellers and diffusers

Noting that by stacking impellers and diffusers (multi-stage), the desired delivery head (TDH- Total Dynamic Head) is achieved.

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3.5 Manufacturers

There are different ESP service providers such as:

- Schlumberger: REDA [3.2]
- Centrilift: Baker Hughes [3.1]
- Weatherford
- Wood Group: ESP
- ALNAS (Russia)

Each pump manufacturer publishes pump curves that describe the relationship between head and flow rate. These curves are usually published for ONE STAGE, for a reference speed and at a std. Specific Gravity (water) (1.00)

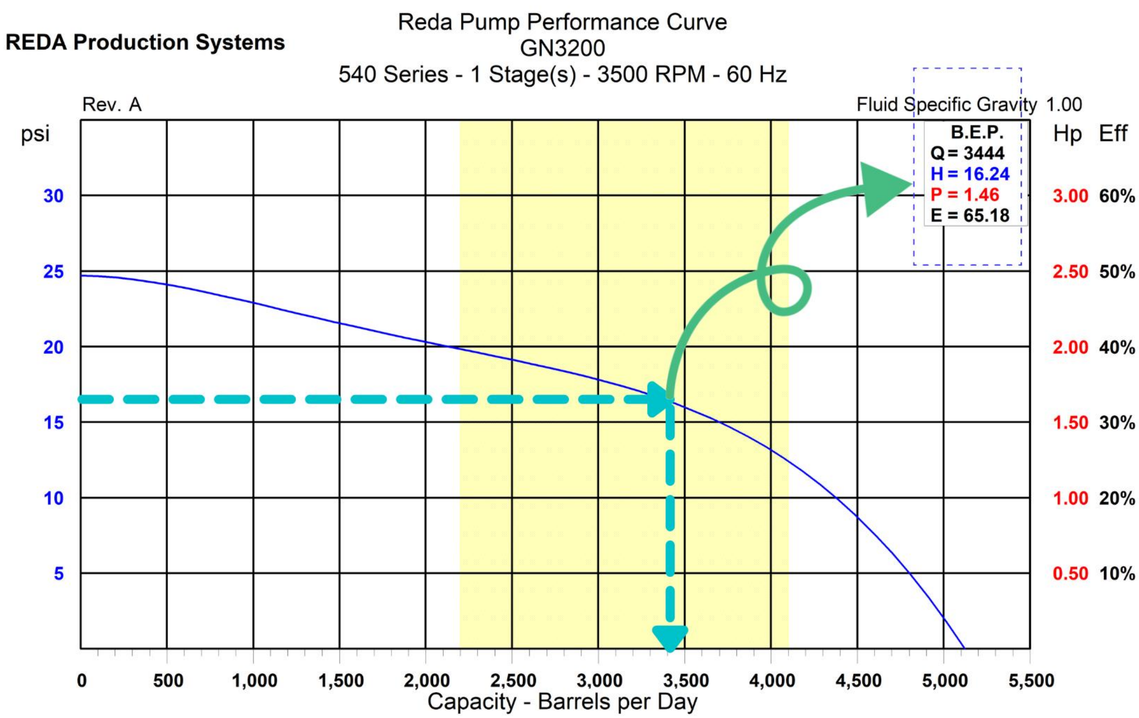

Figure 3. 14 showing pump curve of REDA GN3200 pump that describe the relationship between head and flow rate [3.2]

The figure is an example figure which illustrates the curve of head vs flow rate while it shows the operating point at flow rate of 3444 bpd, head of water of 16.24 ft, power of 1.46 HP, efficiency of 65.18%.

Regarding the pump components, we will discuss the following. For surface control it supplies power to the ESP motor and protects downhole components. However, motor control designs vary in complexity from very simple and basic to very sophisticated, providing numerous options to enhance methods of control, protection and monitoring of operation. Subsea systems have a wide power range and are one of the most versatile lift methods. Standard electric surface drives have ratings from 150 to 150,000 bbl/d

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(24 to 24,600 m3/d) and variable speed drives increase pump flexibility. High GOR liquids can be handled, but large amounts of gas can block and destroy the pumps. Corrosive liquids are handled by using special materials and coatings. Modified equipment and processes allow pumping of sand and abrasive particles without adverse effects [3.3]. To maintain optimum alignment of the flow path between the impeller and diffuser, the impeller is designed to maintain a downward thrust position throughout the operating range

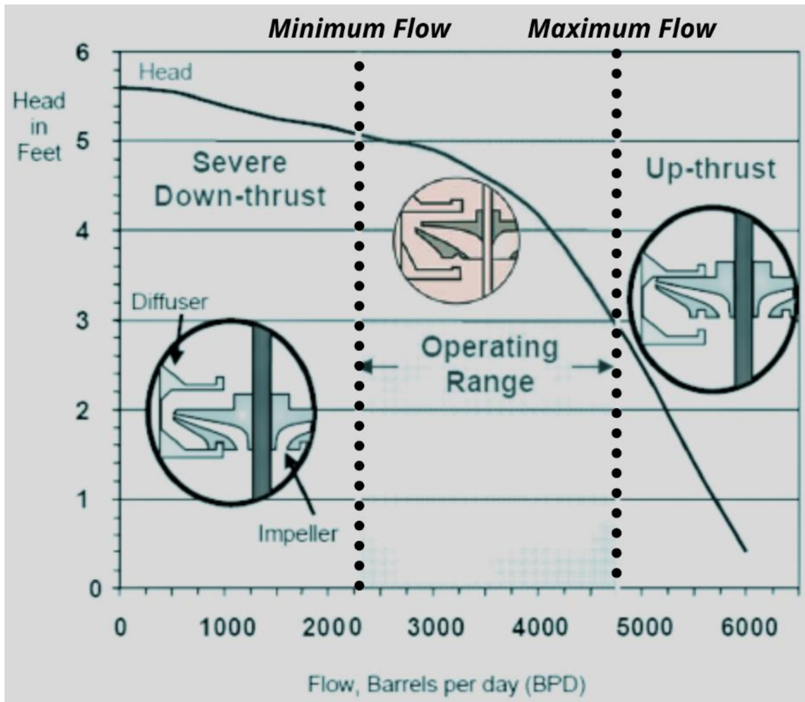

Figure 3. 15 Showing impeller position in different flow rate ranges and the importance of the range selected by manufacturer

The figure above is an example figure which illustrates the curve of head vs flow rate while it shows the operating range of flow rates above or below which the pump will face a mechanical problem that will lead to its breakdown.

Manufacturers quote pump performance data based on 1 stage, 1.0 SG water at 60- or 50-Hz power. A typical performance chart is shown in Figure below. Head, braking power (BHP), and stage efficiency are plotted on the x-axis against flow rate. The efficiency of the pump is given by:
The head/flow curve shows the head or lift, measured in feet or meters, that can be produced by a stage. Since the head is independent of the liquid SG, the pump will produce the same head for all liquids except liquids that are viscous or carry free gas. When the head is plotted in terms of pressure, there is a specific curve for each liquid, depending on its SG. The highlighted area on the graph below is the manufacturer's recommended operating range. It indicates the range in which the pump can be reliably operated. The left edge of the range is the minimum operating point and the right edge is the maximum operating point. The best efficiency point (BEP) lies between these two points and is the point where the efficiency curve peaks. The shape of the head/flow curve and the thrust characteristic of the particular

stage determines the minimum and maximum points. The minimum point is usually where the head curve is still rising before it flattens or drops and at an acceptable downward thrust value. The location of the maximum point is based on maintaining an impeller performance equilibrium, taking into account the thrust value, the head produced and the acceptable efficiency.

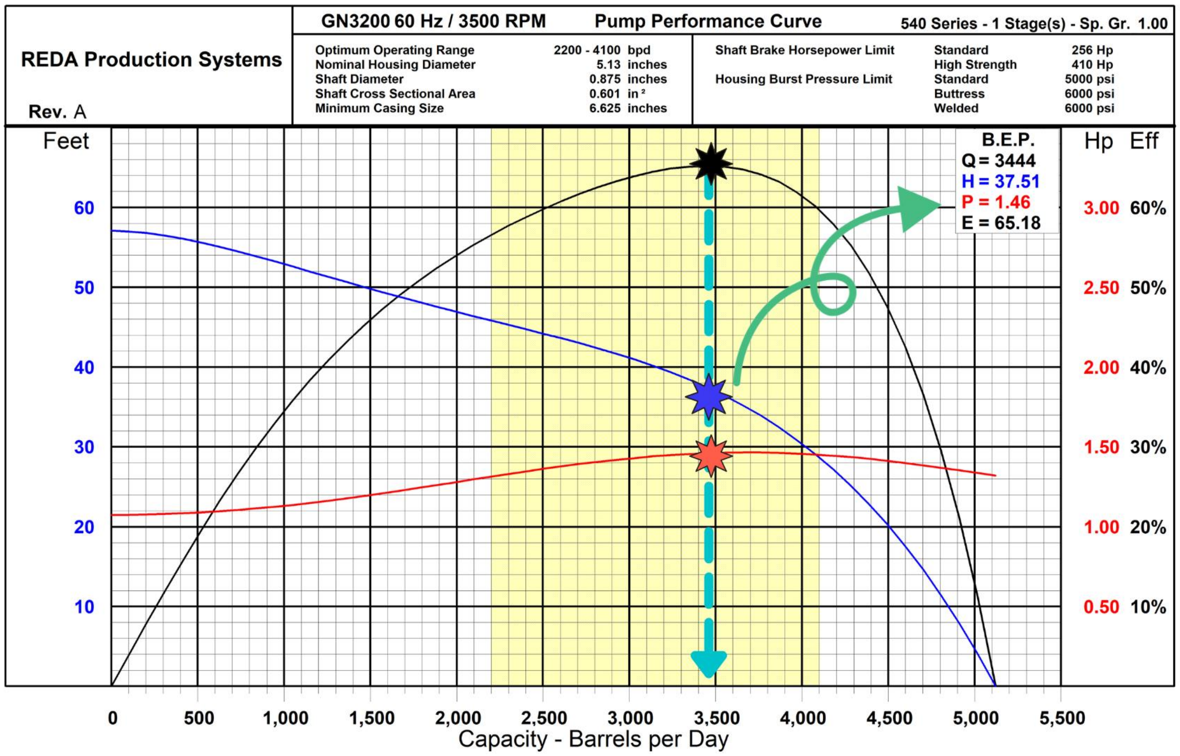

Figure 3. 16 showing pump curve of REDA GN3200 pump that describe the relationship between head/efficiency/power vs. flow rate [3.2]

The figure is an example figure which illustrates the curve of head /efficiency/power vs flow rate while it shows the operating point at flow rate of 3444 bpd, head of water of 37.51 ft, power of 1.46 HP, efficiency of 65.18% as indicated by the points (black, blue, red)

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Figures 3. 17- 3. 18 showing Actual flow rates of liquid, water, oil and gas from a well in Anaconda field with ESP installed

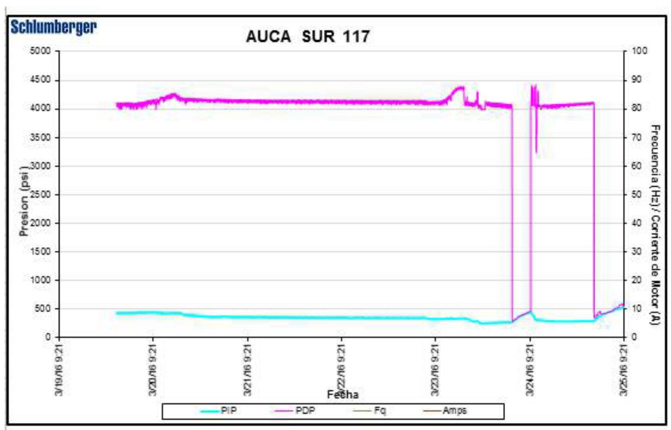

Figure 3. 19 showing measurements took from an ESP pump operating in Anaconda field.

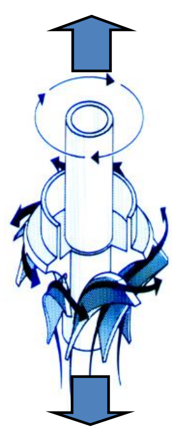

Figure 3. 20 showing fluid passing next to impeller of an ESP

Noting that, the downhole components are suspended from the production tubing above the wells. In most cases, the motor is located at the bottom of the work string. Above the motor are the seal section, the suction or gas separator, and the pump. The power cable is clamped to the hoses and is plugged into the top of the motor. When the fluid enters the well, it must flow past the motor and into the pump. This fluid flows past the motor and helps cool the motor. The fluid then enters the intake port and is drawn into the pump.

3.6 Other components

Radial Mixed Separator Seal Motor Sensor

Figure 3. 21 showing cross section of radial ESP, Mixed ESP, Separator, Seal, Motor, Senosr

3.6.1 Gas Separators

Figure 3. 22 showing gas separator cross section

Gas separators are used in applications where free gas affects pump performance. It consists of devices that separate a portion of the free gas from the liquid flow entering the pump to improve pump performance

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3.6.2 Transformer

Figure 3. 23 showing different transformers used for ESP

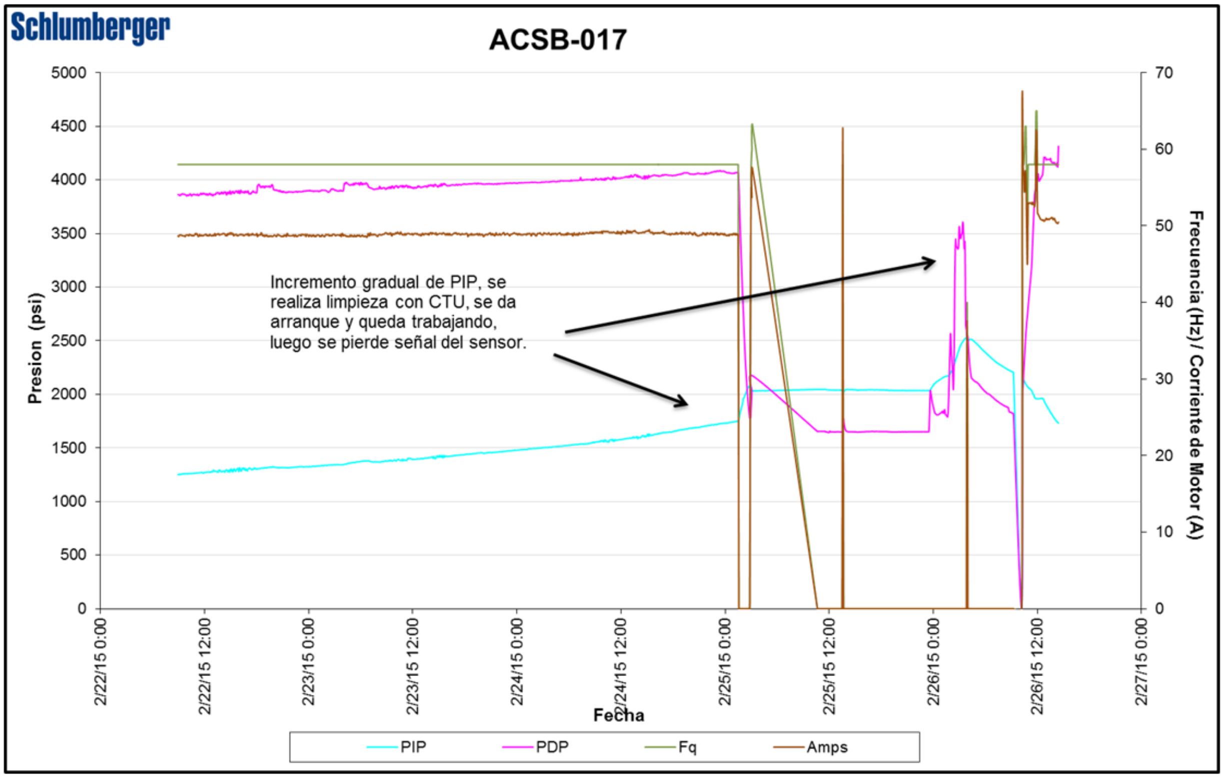
The transformer is a device that converts the voltage of an electrical system. For example, a transformer that converts 7200 volts to 480 volts. This is achieved by two sets of coils wound around an iron core in the transformer. In this case, the transformation ratio is 7200/480. Transformers are rated in KVA power. This depends on the voltage and current that the transformer can handle. KVA = KV * A
KV = Voltage in kilovolts A= Current in amperes

3.6.3 Motor controls

Figure 3. 24 showing motor controllers all components

Different controllers of the Motor are available. They are:

- Fixed Speed Controller
- Variable Speed Controller



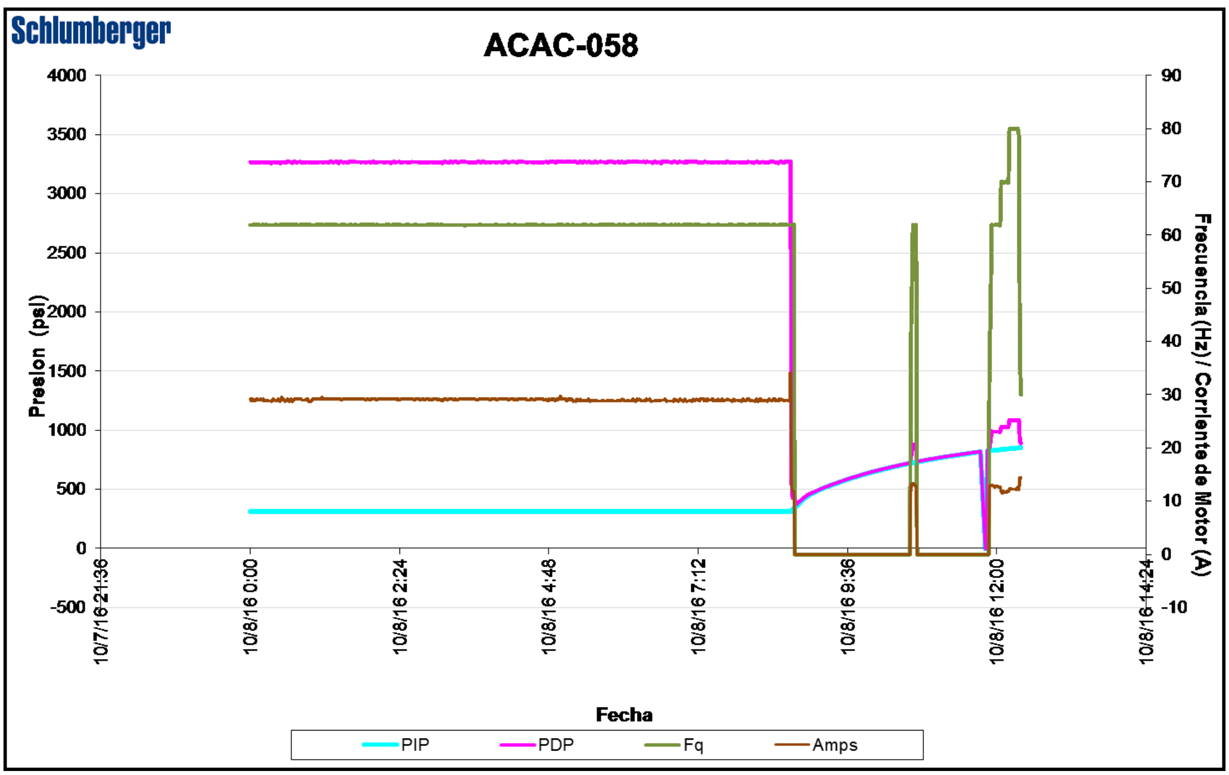


Figure 3. 25-26 showing readings from VSD for pressure/current/frequency vs. time from field data from a field in Ecuador

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3.6.4 Seal Chamber Section

The component located below the lowest pump section and directly above the motor is, in a standard configuration ESP, the seal chamber section. It is basically a series of protection chambers connected in series or in some special cases in parallel. This component has several functions that are critical to the operation and life of the
ESP system and the engine in particular.

-Protects the motor from contamination by the well fluid.
- Balances the pressure between the wellbore and the motor
- Absorbs the axial thrust generated by the pump and dissipates the heat generated by the thrust bearing. [3.4]

Figure 3. 27 showing Seal

3.6.5 The motor

Motor is filled with a highly refined mineral oil that provides bearing lubrication and thermal conductivity(cooling). It is rated two-pole, three-phase squirrel cage induction motor, 3,600 rpm (revolutions per minute) at 60 Hz. It operates on three-phase current at voltages from 230 to 5000.
Generally, the length and diameter determine the motor's performance. Since the motor has no power cable, it can be made in diameters slightly larger than the pumps and seal chamber sections and still fit in the same housing bores. Motor components are rated for temperatures up to 500oF

3.6.6 The power cable

There are several types of cables available in the industry. These include;

- Round cable
- flat cables

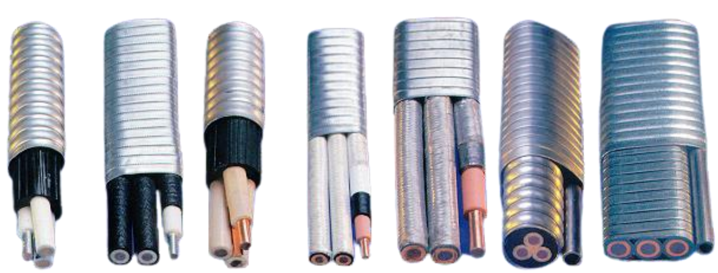
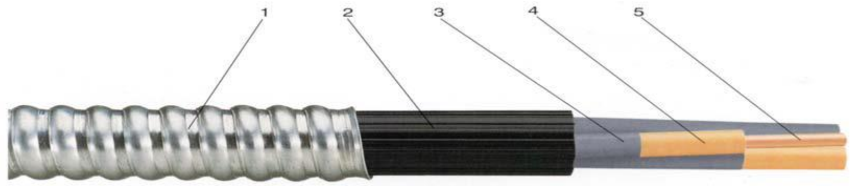


Figure 3. 28 showing different cable types

In addition, the number of conductors also varies from 1,2,4 etc. depending on the company cables also the type of insulation vary based on the working environment, whereas, there are special cable insulation for corrosive liquids and severe environments.



1=Armour, 2=Jacket, 3=Basic insulation, 4=Physical filler, 5=Conductor

Figure 3. 29 showing different parts in a rounded cable

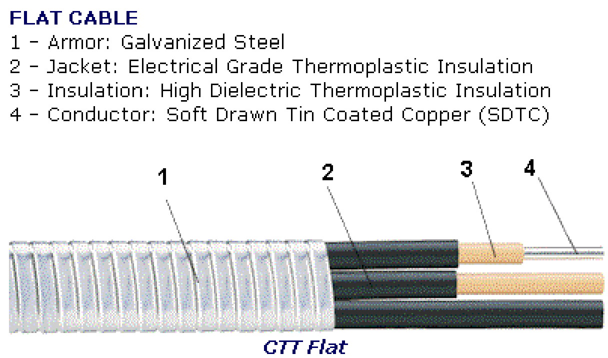


Figure 3. 30 showing different parts in a flat cable

The power cable ESP transmits the required surface power to the motor ESP. It is a specially constructed three-phase power cable designed specifically for the downhole environment. The cable must be small diameter, protected from mechanical stress, and insensitive to physical and electrical degradation from the aggressive downhole environment. The round design is the best conductor, but the flat design is often used under the ESP packer and along the pump and seal section because the space between ESP and the casing is small.

3.7 Virtual flow meter using ESP

3.7.1 Background of virtual flow meter using ESP

In recent years, engineers have applied artificial intelligence (machine and deep learning) to a variety of problems ranging from intelligent transportation systems to online condition monitoring.
ESP applications in systems include predicting multiphase flow rates in wells for real-time monitoring and performance optimization. Currently, the expansion of the benefits of downhole sensors is leading the oil and gas industry to adopt dynamic data-driven application systems in artificial intelligence like machine learning, and deep learning with Big Data tools to gain a competitive advantage.
With the oil and gas industry embracing artificial intelligence (machine and deep learning) and Big Data tools, new inventions and methods are being developed by ESP operators to gain competitive advantage.

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Virtual metering technology is widely used to help operators of ESP -based well systems optimize ESP production and extend ESP runtime. Moreover, electric submersible pumps (ESP) equipped with single and/or multi-point sensors and advanced communication systems have helped in:

- optimize production,
- reduce or eliminate intervention,
- and increase oil recovery factors.

A problem was raised since the increasing need for:

- improved efficiency,
- improved lifetime
- cost reduction

through the use of real-time downhole sensor data makes the operational management of electric submersible pumps (ESP) one of the most important issues in production optimization and enhanced oil recovery.

On another hand, direct physical measurements are not available in many occasions, or do not match process performance because of:

- sensor failure,
- unavailability of technology,
- unreliability of the device,
- or for economic reasons.

In such situations, a convenient substitute for physical sensors would be the use of virtual sensors that use available data during known conditions in instrumented wells to predict other measurements. Such as virtual gauges or soft sensors. [3.5] Virtual metering technology aims to estimate three-phase gas-oil-water flow rates by using physical and/or data-driven models along with low-cost, real-time measurements of process parameters.

Moreover, an advantage of the usage of virtual flow meters is that since well monitoring is essential for reservoir characterization, management of production potential, and selection of activities to increase production. The key to monitoring is understanding downhole flow conditions (i.e., flow rates and flow status). Typically, well rates (i.e., oil, water, and gas) are not measured directly on a continuous basis, with virtual sensors, it is possible to create and implement a continuous well rate estimate (WRE), also known as a virtual rate estimator (VRE). Virtual rate measurement is one type of virtual sensors. [3.6]
A disadvantage of using a trained virtual flow meter, since most oil and gas wells have a transient process where the boundary conditions may change with the life of the well, it is probably safe to assume that the virtual sensor model is not valid for the entire life of the well, ***but only for a certain period of time***.

Noting that virtual flow meters were used since the past. One form of these virtual flow meters is the nodal analysis model which is a class of virtual rate estimators that is well known in the oil and gas industry and it is derived from physics-based models.
This rate estimation requires consistent pressure-volume-temperature (PVT) data, accurate sensors, production well tests.

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In this type of model:

- missing data,
- biased data,
- or failed sensors

can destroy the rate estimate, and a new calibration is required [3.7]
In addition, the uncertainty of the sensor input and the reliability of the rate estimate are often overlooked in these approaches [3.8]

However, the fusion and assimilation of massive well monitoring data poses a major challenge for predicting state variables that cannot be directly estimated by measurements in ESP well systems.
A trained user must be able to interpret the available information about the ESP -based well systems and make reasonable assumptions for other inputs.
The computational engine behind the ESP -based well system performance simulations iteratively solves a set of algebraic and/or differential equations for conservation of mass, momentum, and energy.

For complex, multiphase ESP systems, the computational time required for the convergence of the calculations is not negligible. Therefore, the speed of ESP -based well system simulations is a hindrance to meaningful exploration of a large design space through parameter or optimization studies, which may require hundreds or thousands of simulations depending on the number of variables.

The ESP -based well system can be modeled based on:

- well fluid properties,
- well temperature profile,
- wellbore survey,
- equipment performance ESP,
- reservoir inflow performance (IPR),
- pump setting depth,
- pipe and casing size,
- pipe pressure,
- casing pressure,
- desired flow rate.

As we might know in artificial intelligence can be used to reduce the time needed for the operation.
we have different approaches of which we have data driven approach, physics based approach and hybrid approach which includes both.
One of the shortcomings of the conventional data-driven approach is that artificial intelligence algorithms (machine and/or deep learning) are completely separated from physics-based modeling due to the lack of domain knowledge.

In the conventional data-driven approach:
the software solution takes a set of inputs and returns a set of fluid flow information as outputs.
The outputs are typically a time series over a period of sensor (process) data.
This time series is then compared to historical well flow data to assess its consistency and update the model parameters. One of the shortcomings of the conventional data-driven approach is that the machine

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learning algorithms are completely decoupled from the physics-based modeling due to the lack of domain knowledge.
In the following case study, we will use a hybrid approach. In which a physics-based model generates data. The data will be trained in a data driven approach. In order to predict multiphase flow rates.
Another case study will cover the root cause of an ESP stoppage. but before we proceed into the case study, we will cover some factors that can affect the service life of an ESP.

3.7.2 Factors affecting ESP service life

Factors on which service life depends are listed below:

1) Design and sizing.
   Proper sizing of the device ESP is the first factor in achieving long life. The unit must be sized to operate within the recommended flow range. To properly size the unit, the well productivity data must be accurate. The consequences of incorrect sizing are that the ESP will run outside the operating range, resulting in accelerated pump wear, risk of motor failure due to excessive gas entrapment, or very low flow rates. Inaccurate fluid data can result in a pump that is designed for the wrong conditions.

2) Operating Practices
   Poor operating practices are a major cause of ESP failures. These can result from a lack of knowledge in operating the pump or an unexpected change in the operating environment.
   Information from the well can be used to provide a better overview of ESP operations and performance. Only 2% of ESPs in the world have downhole sensors, and even those that do have the data often neglect to use it to control pumps. Detailed real-time information about the pump pressures and temperatures experienced by the downhole system can be used to protect, control and optimize the operation of the ESP.

3) BHT
   Downhole temperatures in excess of 105 °C are considered a high temperature application for ESPs. The motor assembly must be checked for clearance at the higher temperatures. Failure to do so will result in shorter component life or reduced MTTF (Mean Time To Failure).

4) Free Gas
   Since ESPs are designed to pump liquids, not gas, the eruption of free gas or alternating liquid and gas slugs can cause operating difficulties. As the velocity of the liquid past the engine decreases, cooling becomes less efficient and the risk of overheating and engine fire increases. In extreme cases, as the amount of free gas increases, the pump will begin to lose head and run dry, which is called gas blocking.

5) Viscosity
   High viscosity of the liquid can cause many problems. The higher the specific gravity of the liquid, the more power the pump requires. High viscosity also reduces the pump's ability to lift the fluid and its efficiency, as the viscous fluid creates more frictional pressure losses in the

hoses, causing the pump to work much harder. The viscosity of pumped fluids can change due to the application of shear forces by the pump. Dense emulsions can form under certain conditions.

6) Corrosion

Corrosion from CO2 and H2S can affect the ESP unit by eroding electrical connections, seals and fasteners long before impeller performance is affected. Proper material selection can avoid these problems.

7) Sand abrasion

Sand production can affect ESP performance by reducing pump efficiency through abrasive wear of the stages. More immediate failures result from increased vibration of the pump shaft, which in turn causes mechanical seal failure and motor burnout due to subsequent fluid migration.

The most effective strategy is to eliminate or reduce sand production. Sand production can be managed through controlled start-up and an understanding of sand mobilization rates. The same sand can be produced repeatedly by the pump without reaching the surface.

Damage to impellers and stages can be reduced by proper material selection and abrasion resistant pump design that provides support and radial shaft stabilization.

8) Foreign material

Foreign material can cause damage or failure of a ESP. Although rare, a foreign object can jam the pump, causing the motor to burn out.

9) Deposits

Scale, asphaltenes, paraffin and hydrates can build up in ESPs. The result can be blocked or restricted pump suction, reduced efficiency of pump stages, or clogging of stages, leading to reduced efficiency and the associated risk of engine fire.

10) Electrical failure

Electrical failures can occur at the surface or downhole. Surface problems, such as a regulator or transformer overload, are easier to troubleshoot than downhole problems that disrupt the power source and require a workover operation to replace ESP.

11) Getting Older

Even if the ESP was operated within design limits and care was taken during operation, there will eventually come a time when certain components reach the point of failure.

The hardware, stages and bearings are usually oversized, so failure is most likely to be caused by "wear parts". Seals wear out over time, motor oil deteriorates, O-rings and joints have a definite life span, and electrical components within the pump and well monitoring package fail. However, there are many examples of ESPs that have exceeded the target life of 5+ years in service.

12) Reliability Issues Specific to higher power units.

Higher HP units are at greater risk. A higher HP unit contains more motor sections and is therefore physically longer than other units. Installation can cause mechanical damage to the units, placing them in the "infant mortality" category of the reliability model. The longer the unit, the higher the risk of damage.

The severity of damage and deviation limits must be more stringent than shorter models. Increased physical protection can be achieved by operating the pumps in a sealed enclosure to protect them from mechanical damage during RIH. This system is much easier to overhaul and carries much less operational risk. High capacity pumps consist of several lower capacity pumps connected in series and are therefore interdependent. This dependency reduces the reliability of the entire system. Reliability is also reduced by the need to supply higher power and torque to one motor, which then feeds the other motors.

Chapter 4

4 Machine Learning modeling and case studies

In this thesis we will present different machine learning techniques which can potentially be used during production and workover.

Three case studies will be presented:

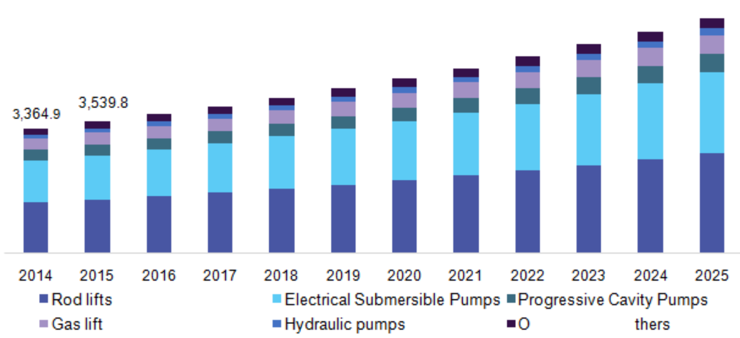
- **Virtual multiphase flow meter from ESP.**
- **Root cause analysis for ESP.**
- **Water/gas injection cost reduction optimization using AI.**

4.1 Case Study 1: Multiphase flow rate measurement from ESP surface reading

In this case study of a physics-based data-driven model and inversion-based methods for model building are developed for ESP well monitoring.

Our design can be applied to gas lift operating wells or other kind of artificial lift methods.
ESP pump was used due to two factors:

1) The fact that the global artificial lift system market size was estimated at USD 16.18 billion in 2016. the Electrical Submersible Pumps (ESP) held the largest revenue share in 2016 and the segment is expected to register healthy growth over the forecast period according to studies made in 2017.[4.1] These pumps are used to effectively pump fluids from wells with low ground pressure. They are widely used in the oil & gas industry due to their small footprint, minimal maintenance, and higher efficiency.
2) We have in this thesis some data provided by an ESP engineer for field data,



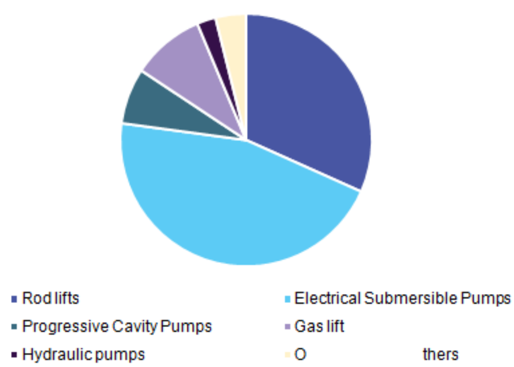


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Figure 4. 1-2. Showing distribution of expected need for different kind of artificial lift methods in US (left), showing distribution of AL methods in China (right) [4.1]

The model is used as a forward engine and an inversion method is then added to interpret the measured data to estimate multiphase surface flow rates. In another word, a python code was built by automating the industry proven Pipesim simulator through developing a python code that uses python toolkit library available in Pipesim then it will retrieve simulation results to an excel sheet which in turn this sheet is feeding another AI algorithm in python in order to predict different flow rates at surface conditions. So, the first part was to generate training and testing datasets and the second part is to use the physics-based datasets in order to predict multiphase flow rates.

4.1.1 Software used

4.1.1.1 PIPESIM [4.2]

PIPESIM (Schlumberger, 2017) is a software used:

- For well planning, production performance analysis, pipeline and equipment design, and network analysis. It is a tool for modeling and simulating petroleum production systems.
- To model many aspects of a field and run a simulation to calculate unknown parameters. Networks with many wells as well as individual wells can be modeled and simulated.

It is a multiphase steady-state flow simulator that models the flow of black oil and compositional modelling.
Also, it is a steady-state multiphase network solver that performs rigorous heat transfer calculations
It also performs simultaneous pressure and temperature calculations.

It has three basic iteration options (where the inlet temperature is always defined):

-Non iterative: Pin (inlet pressure) and Qin (inlet flow rate) known, calculate Pout (outlet pressure).

-Iterate on pressure: Qin (inlet flow rate) and Pout (outlet pressure) known, calculate Pin(inlet pressure)

-Iterate on flow rate: Pin (inlet pressure) and Pout (outlet pressure) known, calculate Qin (inlet flow rate).

Main features of PIPESIM are the following:

- Solution calculated in flow direction
- Each pipeline is divided into an automatically determined number of segments
- Pressure and energy balances in each segment
- Fluid physical properties are calculated at averaged conditions over each segment
- Has a domain PVT, which can generate fluid properties using standard correlations and allows them to be modified to better match measured laboratory data.
- Can be used to model reservoir inflow performance (IPR) and highly deviated

completions, and to optimize all aspects of a completion design, including perforation details, hydraulic fractures, and gravel packing

- Can be used to accurately predict pressure and temperature profiles in producing wells and along surface flowlines.
- Pipesim's sensitivity calculations allow the engineer to easily model and optimize the performance of pipes, chokes, and surface flowlines.
- Can be used to design, optimize and troubleshoot gas lifted wells equipped with ESP.
- Can be used to predict flow rates given the choke size or the choke size for a given production rate and, of course, the pressure drop across a known choke at a given rate.
- Can use multiphase flow correlations fitted to measured field data to generate vertical lift performance (VLP) curves for use in simulators and network models.
- Can be used in a fitting or prediction mode. Fitting of real data is available in PVT, IPR, gradient fitting and VLP fitting.
- Fitting mode, real data can be input and fitted using nonlinear regression methods to create custom correlations that fit the input data.
- Sensitivity mode, the created correlations can be used to make estimates of future well performance.
- Can analyze a network of multiple wells and surface equipment to predict the performance of each well and the impact of planned surface equipment.

4.1.1.2 Upgrading from OpenLink [4.3]

There is an API for Pipesim called the Python toolkit that came as a replacement for OpenLink in earlier versions. OpenLink was developed from scratch as part of PIPESIM and is not a reimplementation of the earlier interface. Although both aim to provide programmatic ways to interact with PIPESIM, they differ substantially in their methodology. Therefore, there is no direct comparison between their respective classes and methods, although some key points are present:

- OpenLink uses an object-oriented representation of PIPESIM in which model components and operations are operated upon. Updating a value involves manipulating the objects and their properties. Data is always passed between the model and Excel as single values.
- In the contrary, PIPESIM Python Toolkit uses an input/output (I/O) interface which sends and receives information regarding the model.
- Doing changes to a value involves calling a function in order to set the component parameter to a value. Data is passed between the model and Excel as single values and as DataFrames. The toolkit can be used independently of Excel, for example, as scripts that run on the desktop.

In another word, the Python toolkit contains a set of variables and functions that can be called via a Python script, Python being an open source programming language. So by using the Python toolkit, it is possible to create a script to automatically enter parameters into the field model and run multiple simulations. In addition, Functions available through PIPESIM Python Toolkit include:

- Adding and deleting model components

- Changing and updating the parameters of model components
- Convert Junctions to other model components such as wells and sources
- Importing and exporting wells
- Performing tasks such as network simulation, PT profile simulation, and Nodal Analysis simulation. [4.7]

4.1.1.3 Programming language Python

Python is an open-source scripting language available in various distributions and well documented both online and in the literature. It has many third-party extensions called modules that can be downloaded and installed. It is one of the top ten most widely used languages in the world and is actively developed and maintained. Its open-source nature and large library of third-party extensions makes it popular in the scientific community. [4.7]

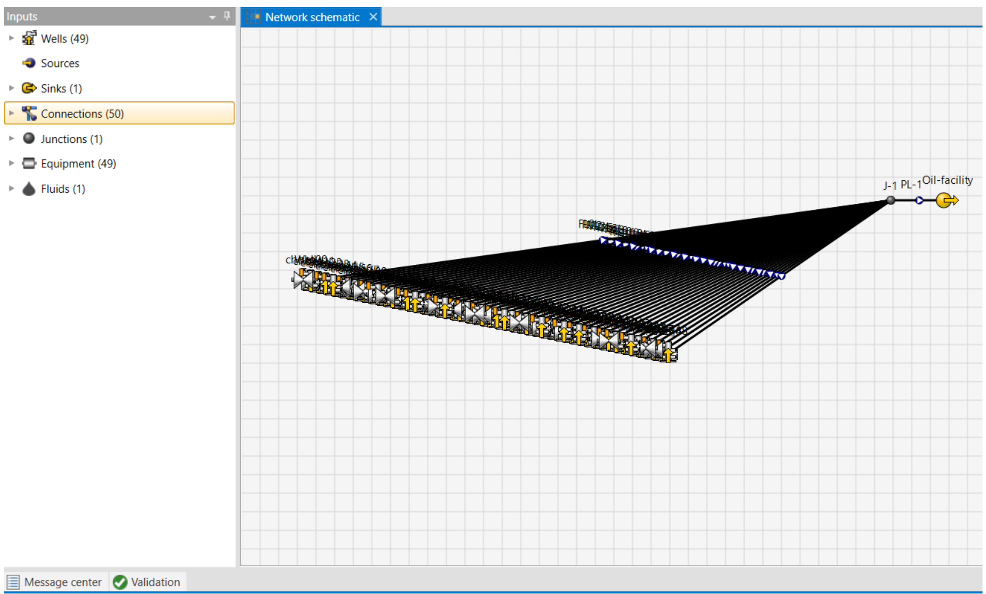

Figure 4. 3 showing a generated network (in this study) using python toolkit of 49 wells simultaneously from a Python script.

Our data of multiphase flow rates at wellhead are obtained from physics based model simulation.
By using Pipesim software, a nodal analysis study was conducted for different and many trials with changing Water cut, pump frequency, reservoir pressure, Reservoir temperature, pump type, number of stages of the ESP pump.
Steps followed re as per the fig below:

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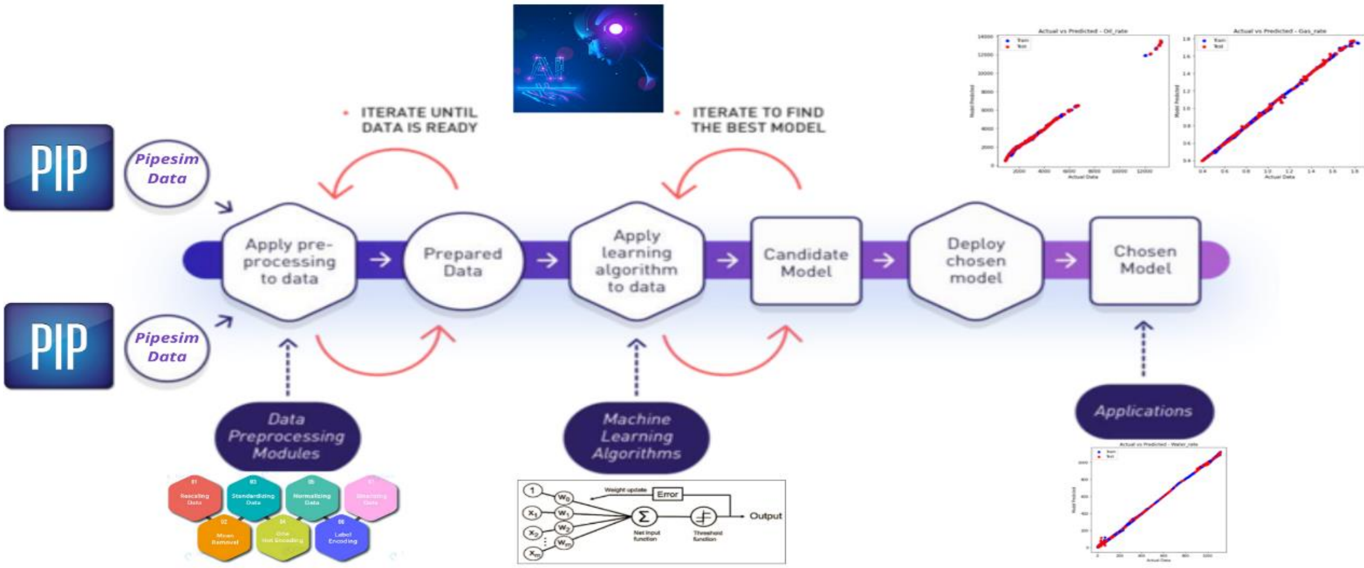

Figure 4. 4 showing a generated network (in this study) using python toolkit of 49 wells simultaneously from a Python script.

These steps consists of:

- Data generation
- Data preprocessing
- Machine learning models implementations including hyperparameters optimization.
- Choosing the best model

4.1.2 Data

4.1.2.1: Data generation

1) Python code was built in order to automate Pipesim.
2) New data Generated which could be hard to extract from Pipesim UI.
3) Same code generated can be used to predict all data from ESP pumps that can be used over the lifetime of a field.
4) By combining reservoir engineering forecasts with operation parameters we are able to predict the different ESP models over lifetime of a field, which can be used at a later stage to optimize number of ESP model used in a field.

`

4.1.2.2 Physics-based model inputs

Different initial features values were fed into each well:

1) Reservoir pressure,
2) upstream & downstream choke pressures and temperatures
3) Gas Liquid Ratio (GLR)
4) Water-Cut (WC)
5) PVT data
6) Well geometry

Noting that the output of the simulation is an excel sheet with the following features: Liquid rate**,** Oil rate**,** Water rate**,** Gas rate**,** BHP**,** Pressure at Nodal Point, WHP**,** WHT, Pump data (such as: Delta pressure, Outlet temperature, Delta Temperature of the pump, Discharge Pressure, Efficiency, Efficiency Factor, Flowrate Factor, Frequency, Head, Head Factor, Intake Gas Volume Fraction, Intake Pressure, Intake Total Volumetric Flowrate, Number Of Stages, Power, Power Factor, Suction Gas Volume Fraction. Thus, the values of each feature will be used by our AI algorithm in order to predict the oil, gas and water flow rates.

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4.1.2.3 Data Visualization

Our generated data are following below shapes and forms and are visualized through various visualization techniques.

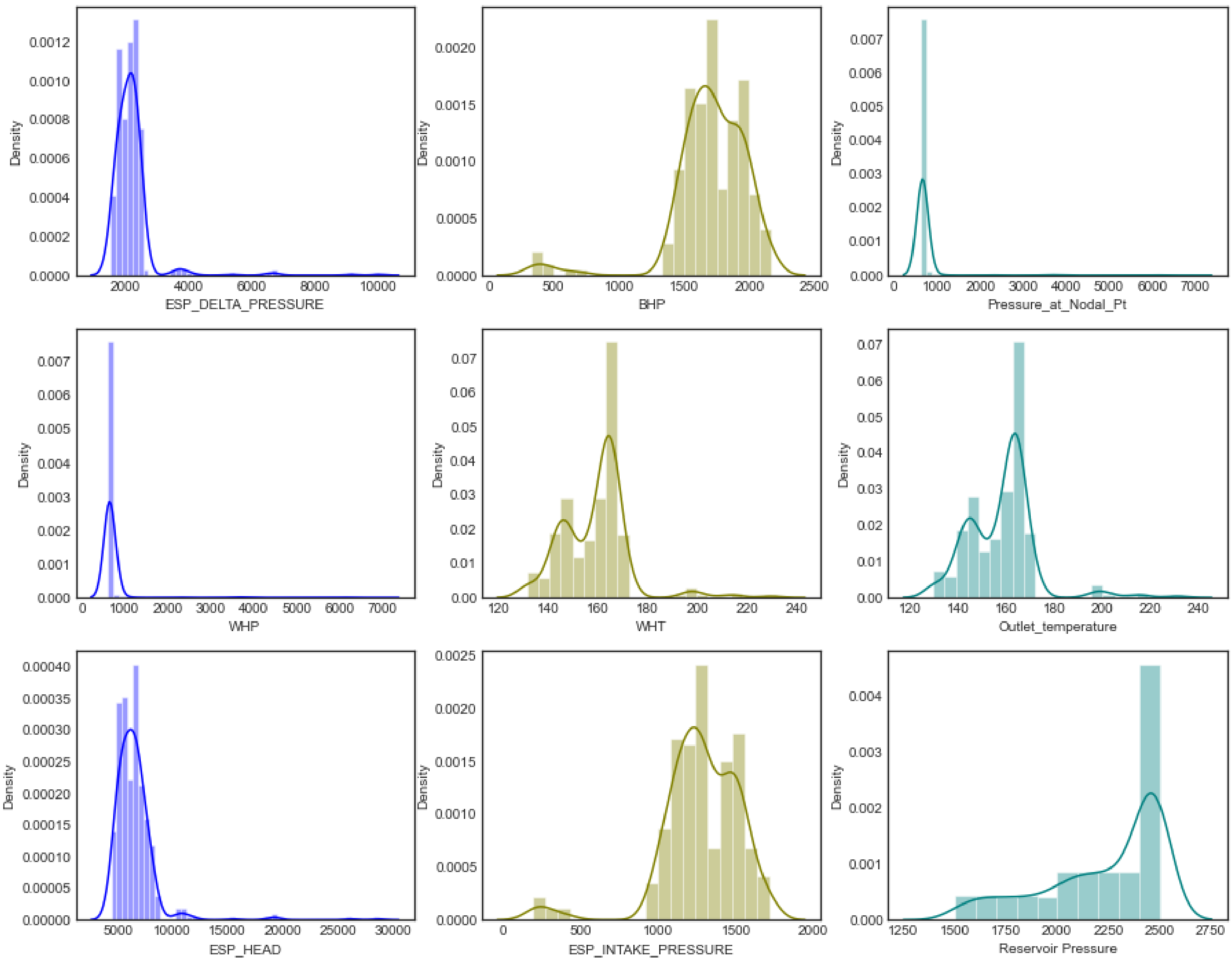

Figure 4. 5 showing features distribution

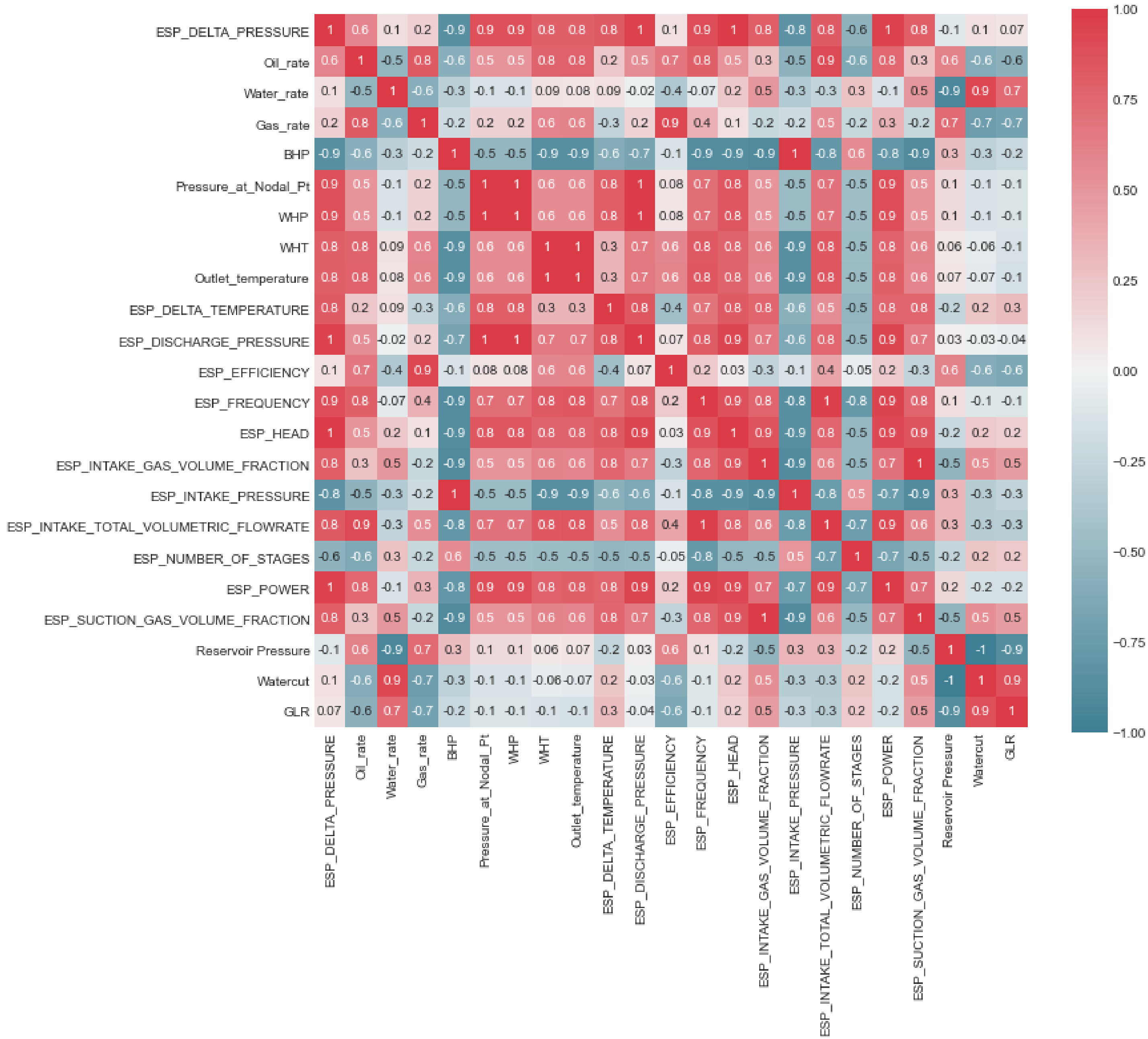

Figure 4. 6 showing the Heatmap plot showing correlations and collinearity between existing variables.

Relationship between Different parameters and flow rates (oil, water and gas)

Strong positive factors for oil flow rate with:

- ESP Frequency (R=0.8)
- Outlet temperature (*R*=0.8)
- Well head temperature (*R*=0.8)
- Intake total volumetric flowrate (R=0.9)
- Reservoir pressure (R=0.6)

`

Strong positive factors for water flow rate with:

- Watercut (R=0.9)

Strong negative factors for water flow rate with:

- Reservoir pressure (R=0.9)

Strong positive factors for gas flow rate with:

- Oil flow rate (R=0.8)

- Reservoir pressure (R=0.7)

4.1.2.4 Data partitioning: dataset splitting

Overfitting is one of the major challenges in training machine learning models. splitting the dataset is considered a necessary step in order to account for overfitting and help models to be more generalized. A dataset is often split into three sets of observations: Training and Test data are considered as a rule of thumb.[4.4]

- Training data: The dataset used by the algorithm to learn the parameters of the machine learning model is the training data.

- Test data: To assess the performance of a fully trained model test data subset is used. Prediction accuracy on test data is an indicator of the model's performance on unseen data encountered in a real-world scenario.

`

4.1.3 Results

4.1.3.1 Feature selection

This section involves selection features that contribute most to the prediction variable or target;
In order to reduce the training time, improve the accuracy of prediction models and avoid the overfitting problems; A method used called recursive Feature Elimination with cross validation: recursively removes features, then builds models using the remaining features and calculates model's accuracy.

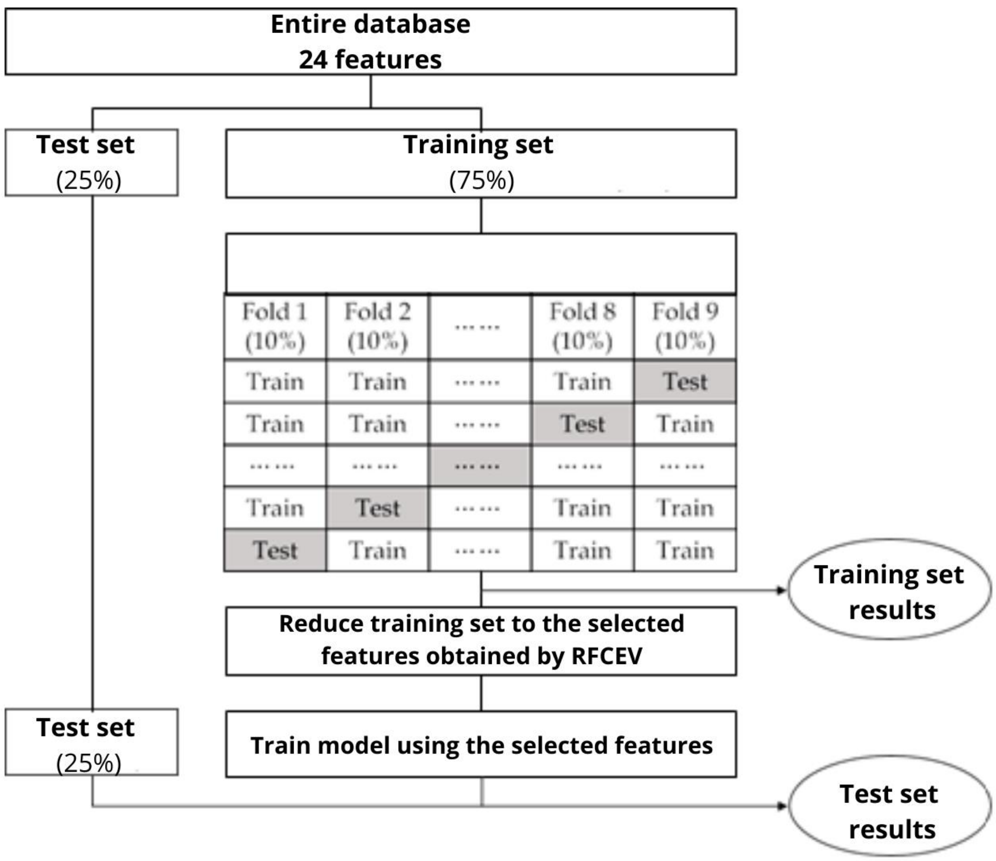

Figure 4. 7: Showing the map of training the dataset

Some observation after features elimination are the following:

- If the number of features is less than 6, the prediction accuracy of the model is significantly reduced;
- The model with 24 features has the largest mean value and a relatively lower standard deviation;

Noting that random forest is used as the prediction model in the RFECV process.

`

So, after eliminating some features based on the previous method, we got the following:

- For gas:
    - trained model rmse: 0.24
    - r2: 0.627
    - test set rmse: 0.285
    - test set r2: 0.45806778040089957
- For Oil:
    - train rmse: 1003.26
    - train r2: 0.808
    - test rmse: 1067.765
    - test r2: 0.766
- For water:
    - train rmse: 200.038
    - train r2: 0.75
    - test rmse: 193.729
    - test r2: 0.769

Starting with Water flow rates: XGBoost is used as the prediction model in the feature shuffling process. Also, the addition of some features affects the performance of the model (positively or negatively) such as shown in the figure below. Important features can summarized as per the following:

- GLR
- Watercut
- Reservoir pressure
- ESP intake pressure

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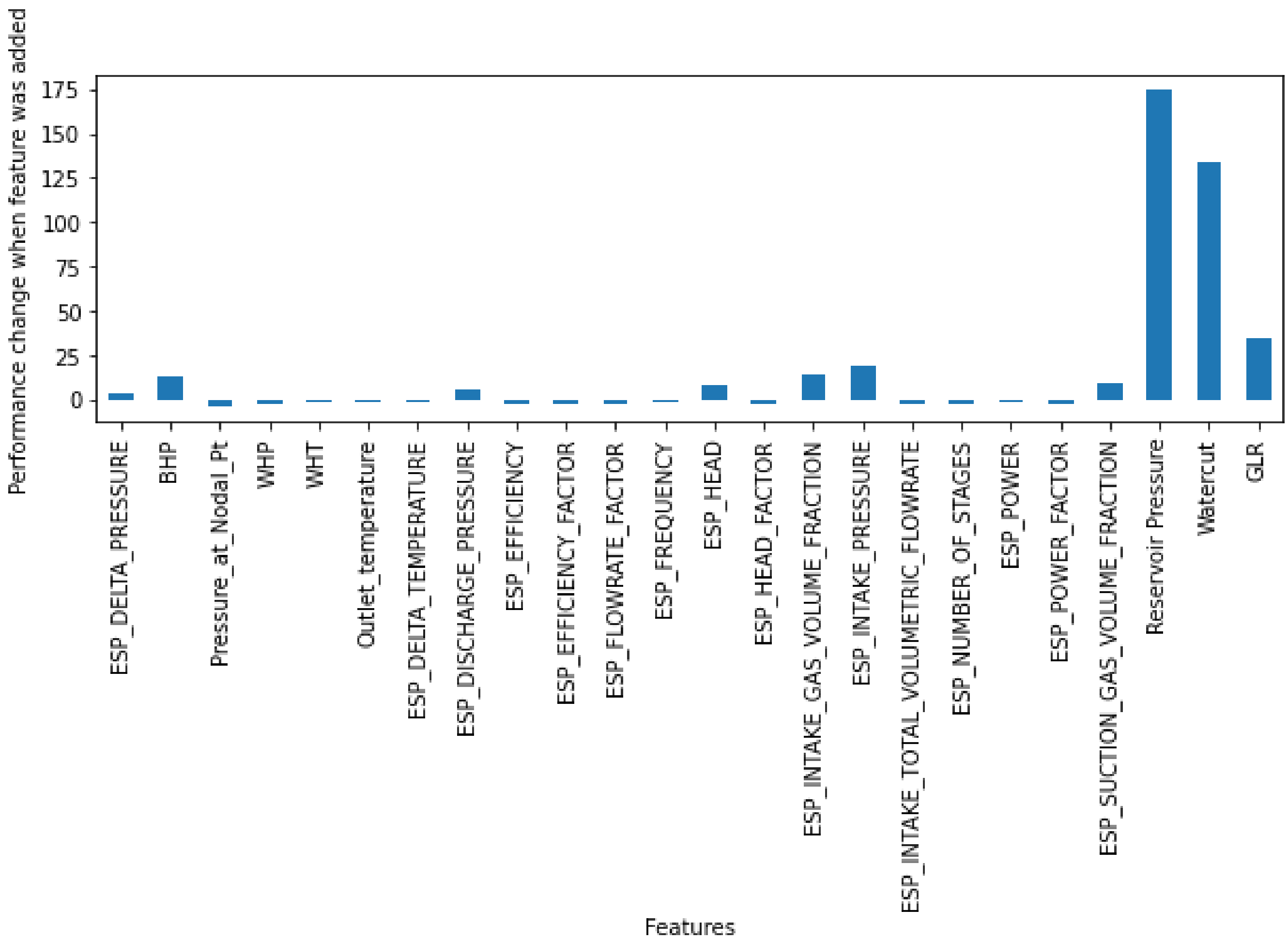

Figure 4. 8: Showing the how the performance changes after addition of each feature for water flow rate.

For water flow rates: 4 most critical features of importance are found. They are as follow:

- Reservoir pressure
- Watercut
- GLR
- ESP intake pressure
- BHP

Noting that the model accuracy with RF with only the 5 features was for:

- Trained set rmse equals to 4.42
- Trained set r2 equals to 0.9998
- Test set rmse equals to 10.2
- Test set r2 equals to 0.9994

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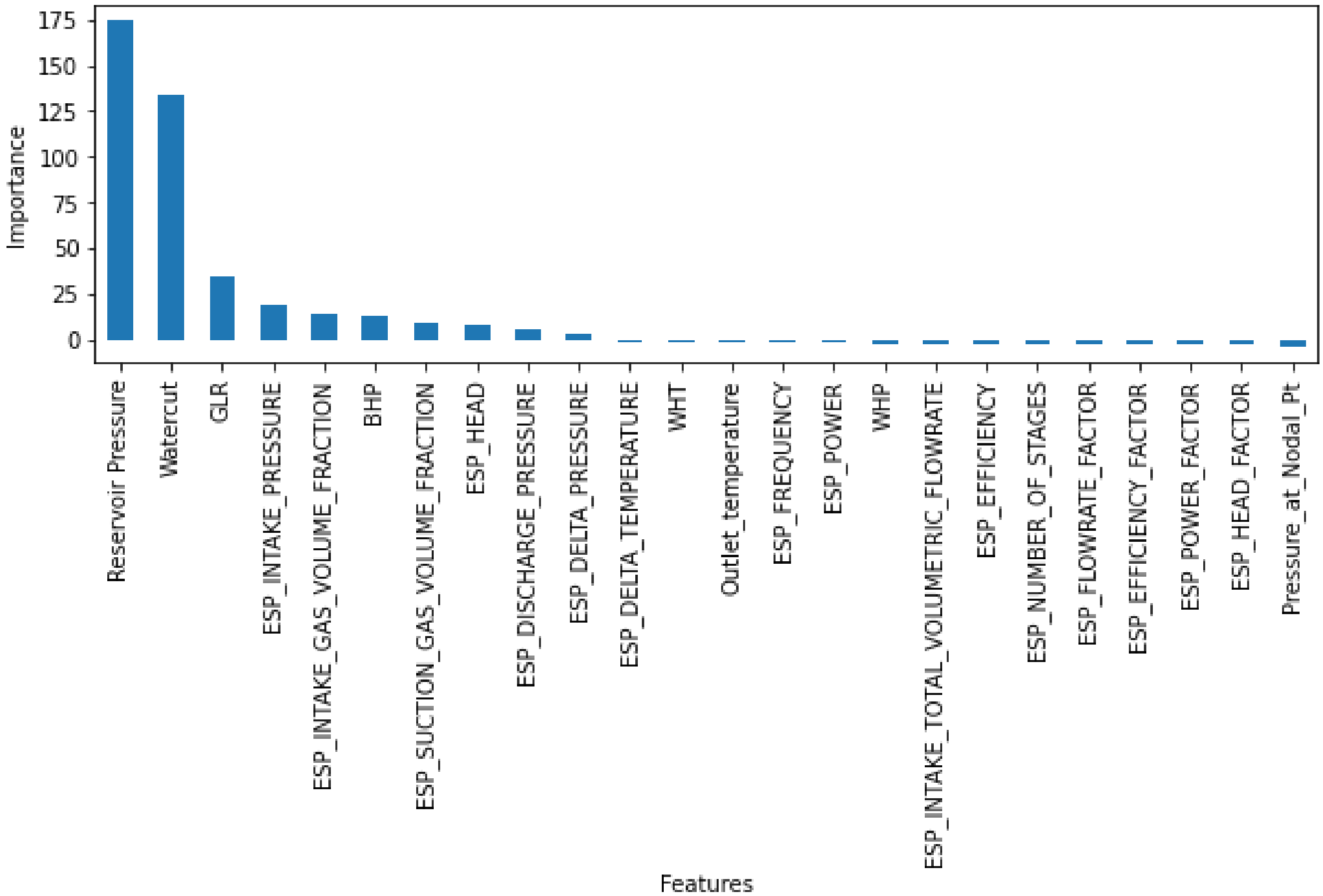

Figure 4. 9: Showing the how the performance changes when recursive feature selection is performed for water flow rate.

For Oil flow rates: XGBoost is used as the prediction model in the recursive feature elimination (RFE) process. the most critical features of importance are found.

- Pressure at nodal point (choke)
- ESP delta Pressure
- ESP efficiency

Noting that the model accuracy with XGboost with all the features included was for:

- Tested set r2 equals to **99.7%**

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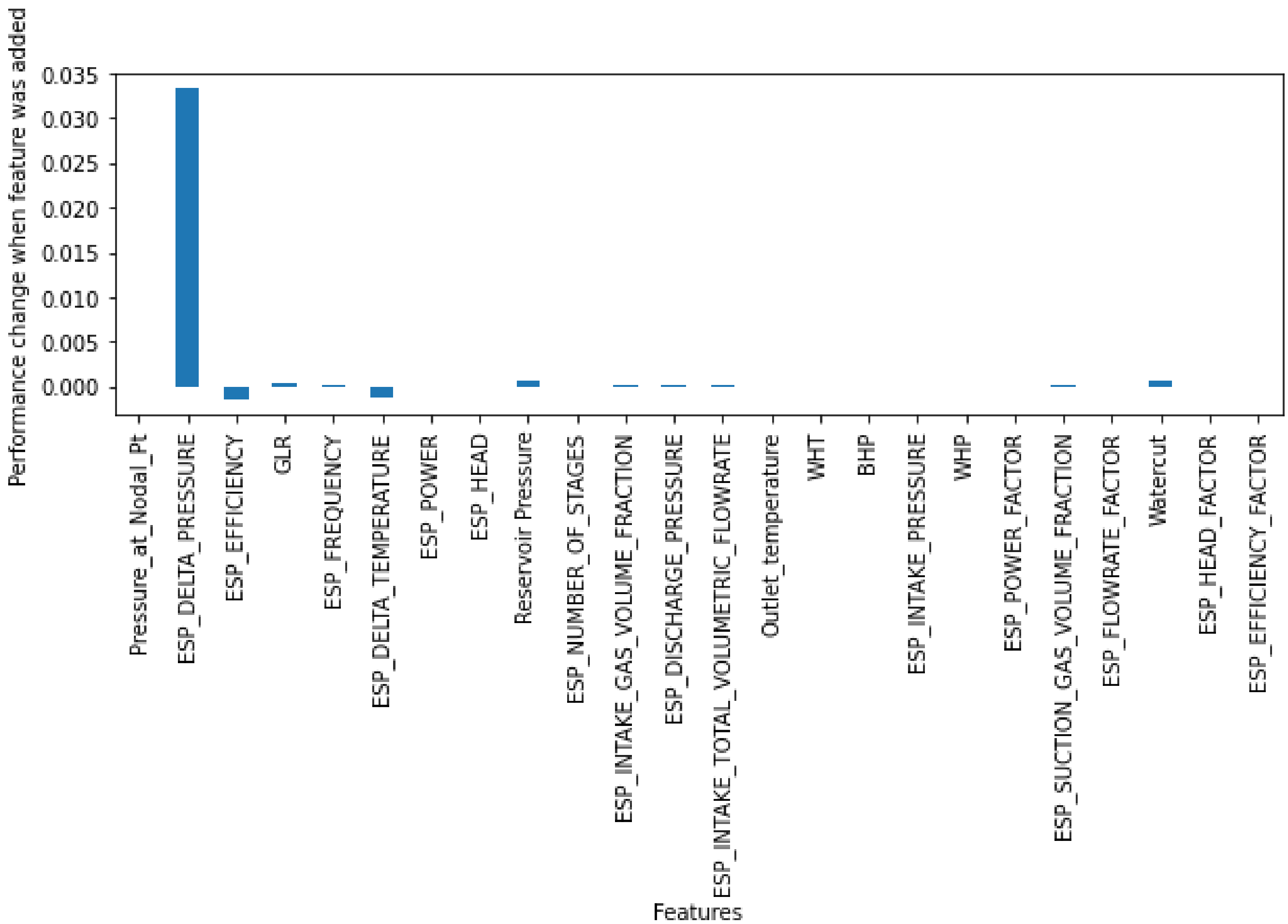

Figure 4. 10: Showing the how the performance changes when recursive feature selection is performed for oil flow rate.

For Oil flow rates, when features are added some features might affect the performance of the model such as shown below for**:**

- ESP efficiency
- ESP delta pressure

While **s**electing only the first two features of the model accuracy with XGboost with all the features included increased little bit to:

- Tested set r2: **99.8%**

`

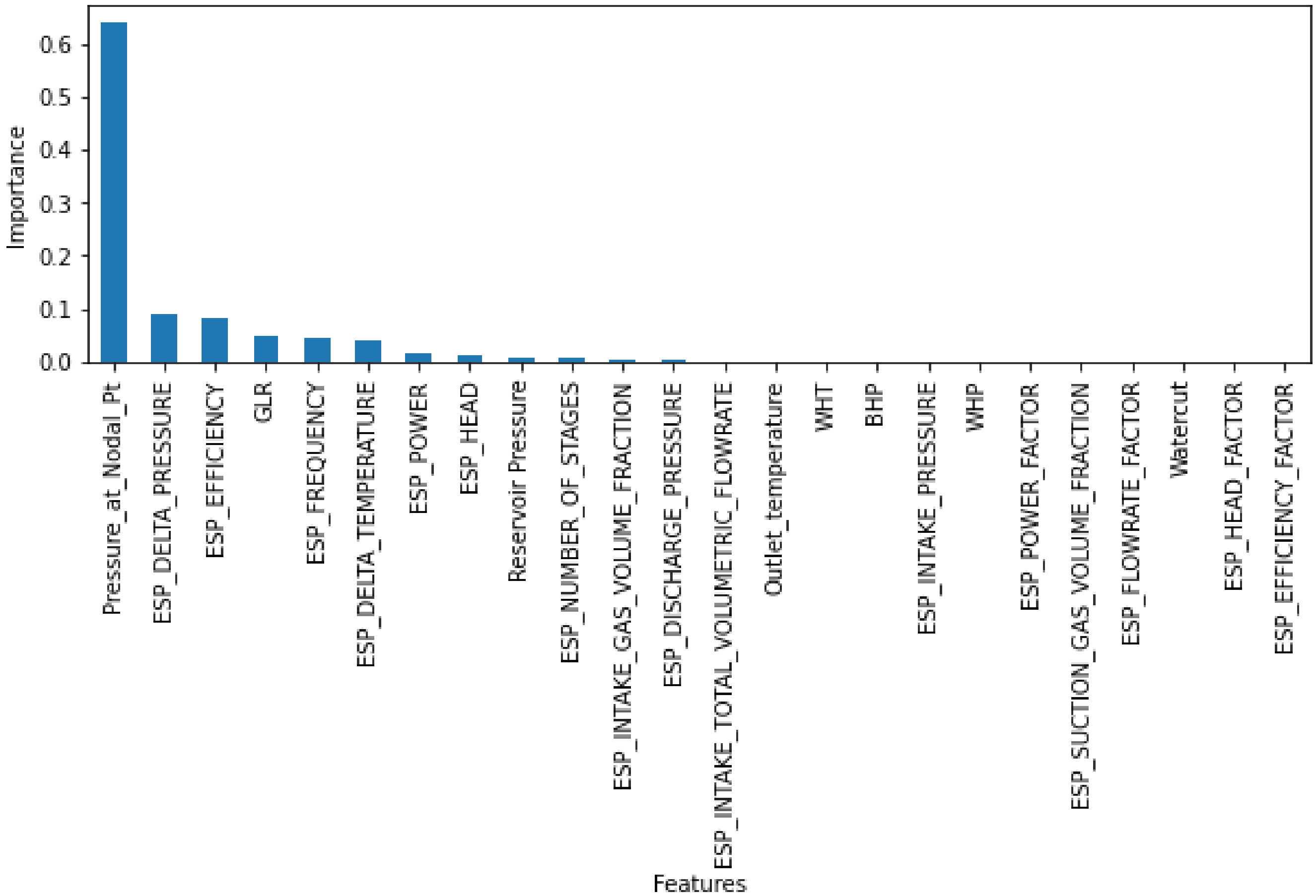

Figure 4. 11: Showing the how the performance changes after addition of each feature for oil flow rate.

For Gas flow rates the addition of some features affects the performance of the model (positively or negatively) such as shown by the figure below the most critical features found for gas flow rate are the following:

- Pressure at nodal point
- ESP delta pressure
- ESP efficiency
- Well head pressure
- GLR
- ESP frequency
- ESP delta temperature

Moreover, selecting through RFE only the first three **features** of the model accuracy with XGboost with all the features included increased little bit to:

- Tested set r2: 99.5%

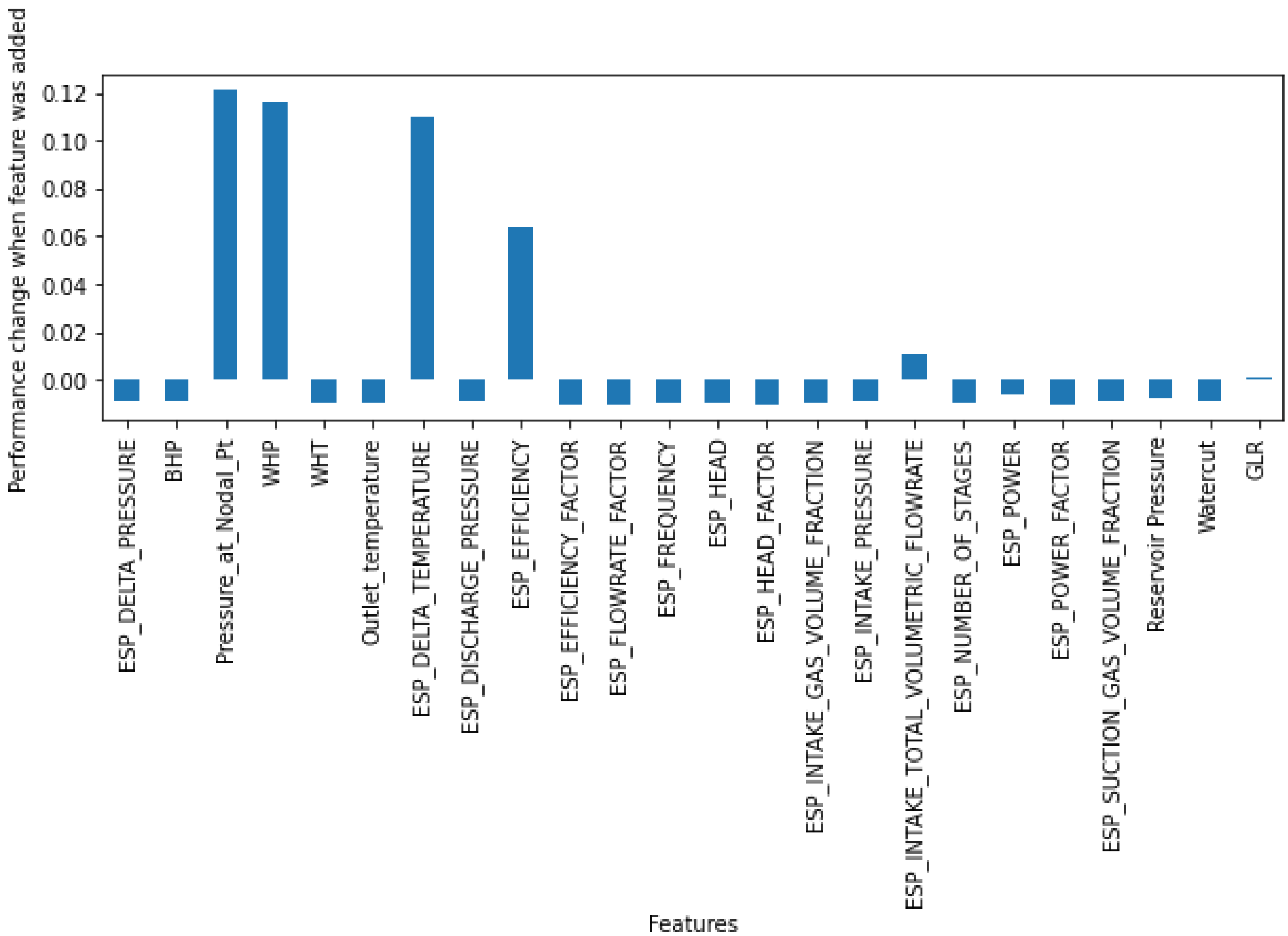

Figure 4. 12: Showing the how the performance changes after addition of each feature for gas flow rate.

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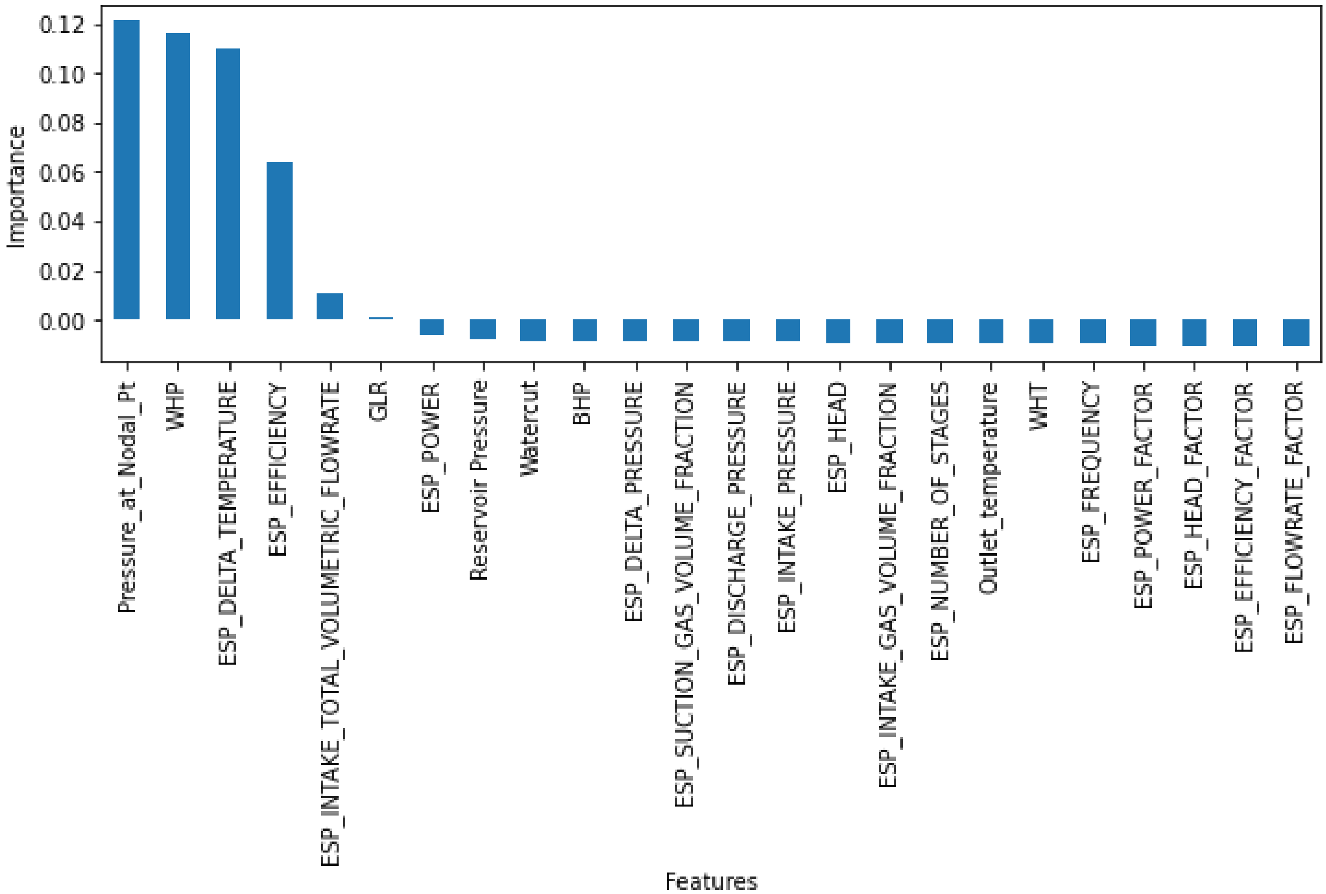


Figure 4. 13: Showing the how the performance changes when recursive feature selection is performed for gas flow rate.

From the figure above we can deduce the distribution of the most important features in the data, which are as the follow:

- Pressure at nodal point (choke).
- Well head pressure
- ESP delta temperature
- ESP efficiency
- ESP intake total volumetric flow rate

4.1.3.2 Support Vector Regression

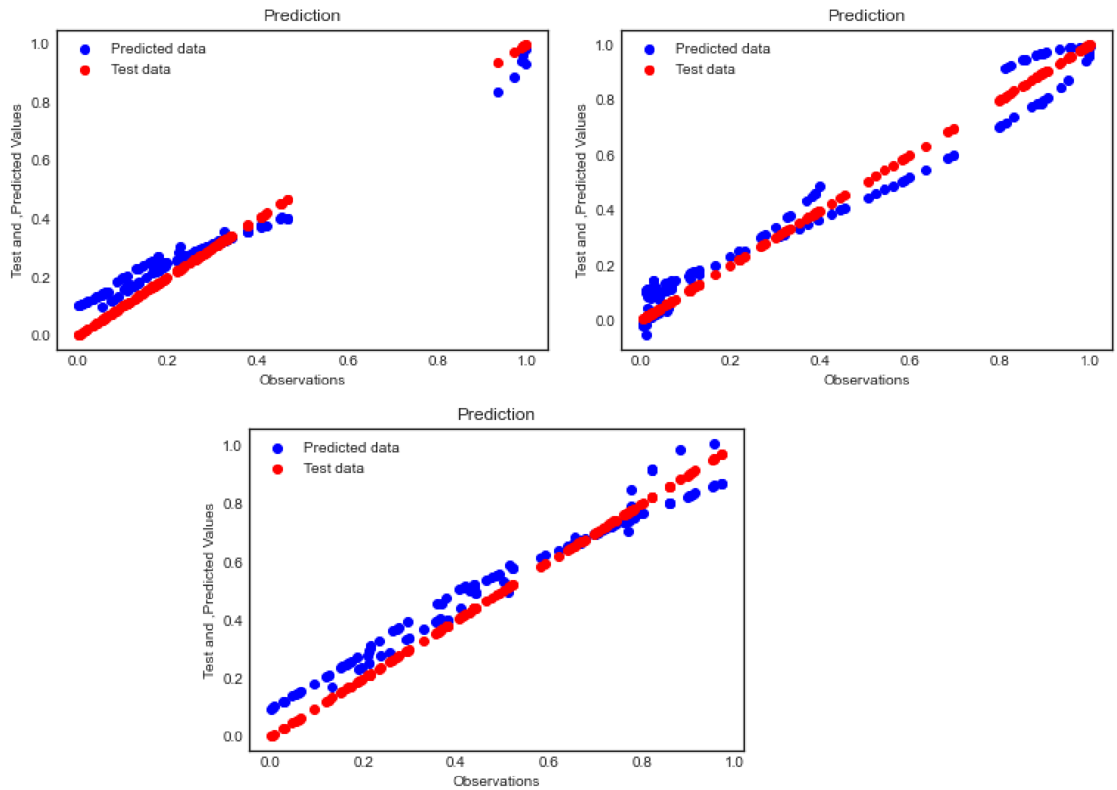


Figure 4. 14- 15- 16 showing predicted result of SVM over test data for oil(top left), water(top right) and gas (bottom)

The support vector regression results are shown in above pictures for oil, water and gas flow rates in blue (predicted data). As per the figures above we deduce that the predicted data shifts far from the test data in the 3 phases. Which in turn means that this AI performed a poor prediction. Noting that the diagonal line in red represents the line of tested data with respected to the tested data.

4.1.3.3 Random Forest Regression

The results obtained with random forest regression show better prediction accuracy than the previously discussed algorithms.

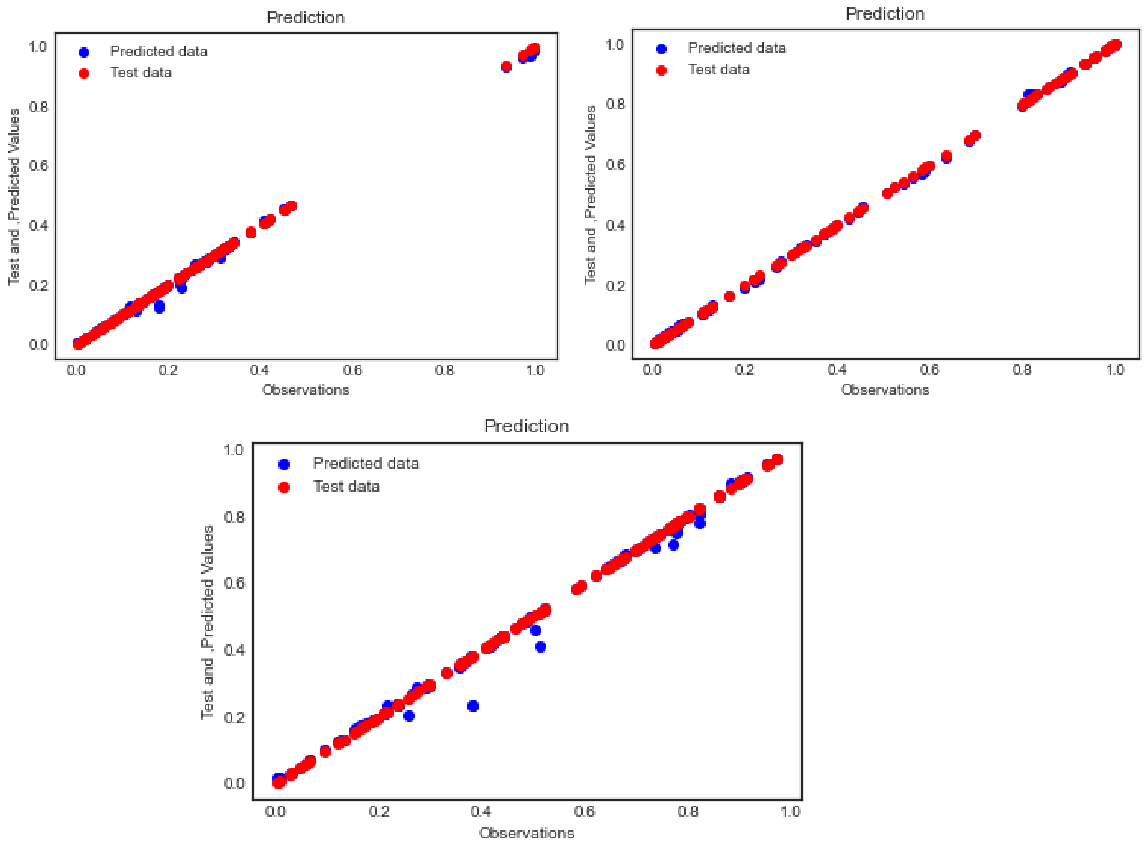


Figure 4. 17-18-19 showing predicted result of Random Forest over test data for oil(top left), water(top right) and gas (bottom)

In the above figures we notice that the predicted data in blue fits perfectly the tested data especially in the water flow rate case. But regarding the oil and gas predicted flow rate, it fits the tested data better than in the previous algorithm but with some minors especially for the gas flow rate prediction. Noting that the diagonal line in red represents the line of tested data with respected to the tested data.

4.1.3.4 XGBoost: eXtreme Gradient Boosting

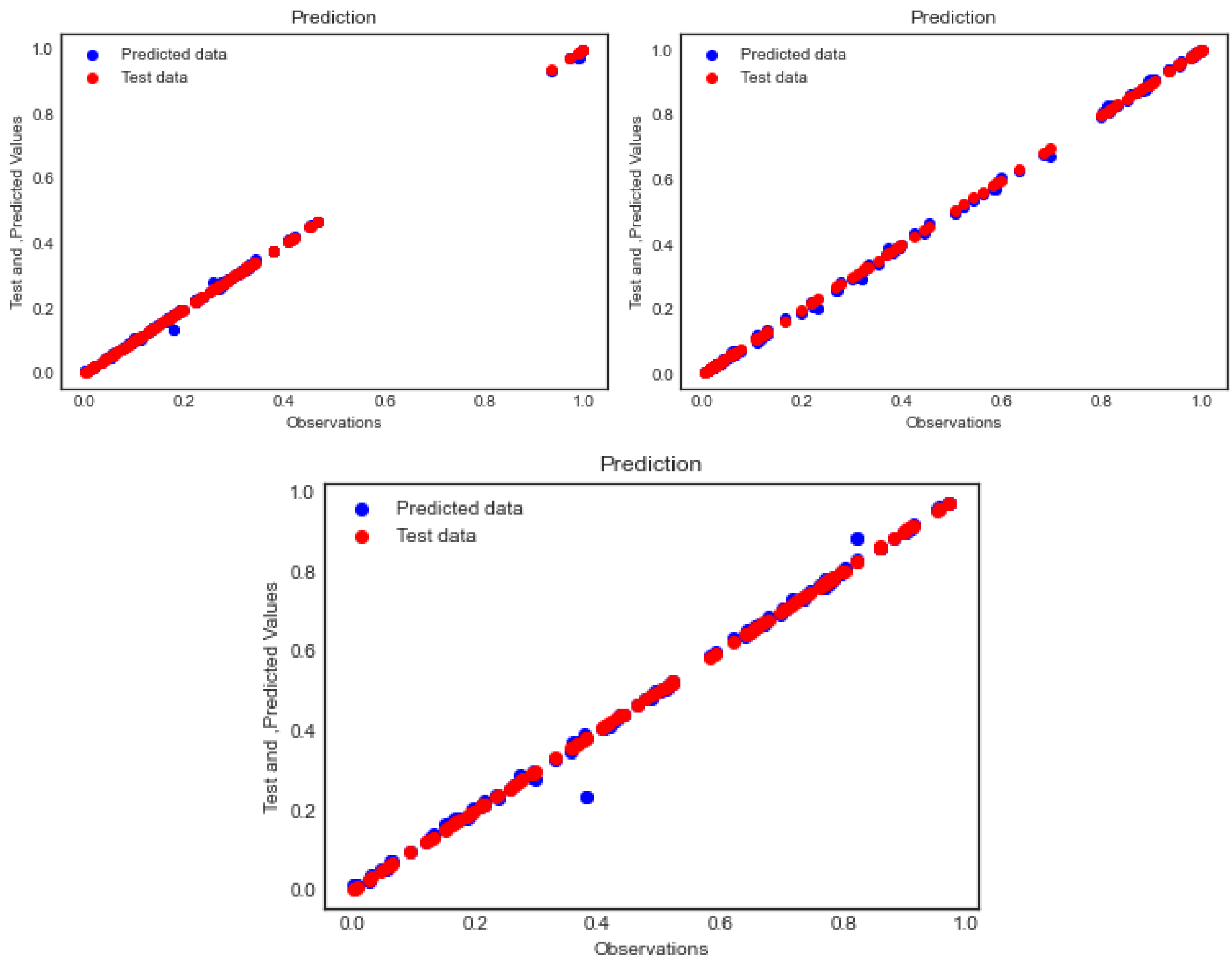


Figure 4. 20-21-22 showing predicted result of XGboost algorithm over test data for oil (top left), water(top right) and gas (bottom)

In the above figures we notice that the predicted data in blue fits perfectly the tested data especially in the water flow rate case. But regarding the oil and gas predicted flow rate, it fits the tested data better than in the 2 previous algorithms with some minor improvements from the random forest algorithm results especially for the gas flow rate prediction. Noting that the diagonal line in red represents the line of tested data with respected to the tested data.

4.1.3.5 Artificial Neural Network

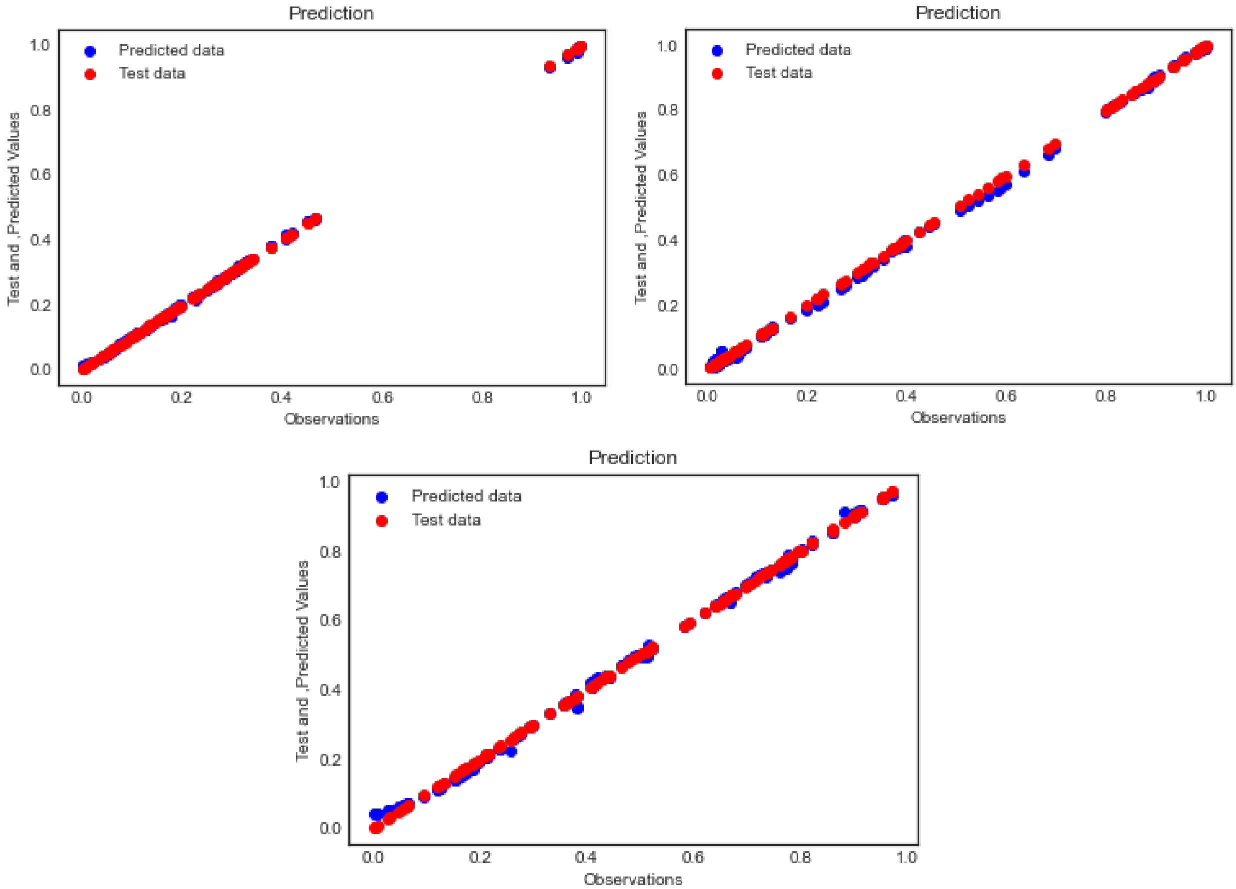


Figure 4. 23-24-25 showing predicted final results of ANN or MLP algorithm over test data for oil(top left), water(top right) and gas (bottom)

In the above figures we notice that the predicted data in blue fits perfectly the tested data in all phases (oil, water and gas) where the diagonal line in red represents the line of tested data with respected to the tested data.

As machine learning models become more complex, the task of training them appropriately becomes more difficult. To adequately train a deep neural network model, we need to follow the process of hyperparameter optimization. Accuracy after hyperparameters tuning for oil, water and gas flow rates achieved a 99% of accuracy as shown per pictures above After that in order to select the correct best algorithm, a model selection was made in which hyperparameter tuning will lead for the best accuracy. Noting that the algorithm used Adam model for optimization of iterations and was designed in order to prevent the vanishing and exploding gradient problem.

4.1.3.6 Comparison of the regression models

To evaluate the performance of ML models, we consider two different common evaluation metrics for regression problems to quantify the predictive accuracy of a model depending on which algorithm performs best.

`

They are as follows:

- the coefficient of determination (R2),
- the root-mean squared error (RMSE).

R2 is calculated with the following equation:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}.$$

(Eq. 5.3)

SSres is the residual sum of squares, and SStot is the total sum of squares, which is mathematically calculated using the following expressions.

$$SS_{res} = \Sigma\left(y_i - y_{reg}\right)^2 ; \quad SS_{tot} = \Sigma\left(y_i - \overline{y}\right)^2 .$$

(Eq. 5.4-5)

Here, yi is the value of each data point, y is the mean, and yreg is the value predicted by the regression model.

On the other hand, the RMSE metric is calculated using the following equation.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(\hat{y}_i - y_i\right)^2}{N}}$$

(Eq. 5.6)

Where ŷi is the value predicted by the regression model and N is the number of observations. Compared to the similar Mean Absolute Error, RMSE amplifies and severely punishes large errors.

Machine learning algorithms	**Average R^2**	**RMSE**
RF (oil)	**0.996**	**0.008**
MLP (ANN) (oil)	**0.998**	**0.0015**
SVM (oil)	**0.92**	**0.06**
XGBoost (oil)	**0.997**	**0.007**
RF (water)	**0.9994**	**0.005**
MLP (ANN) (water)	**0.997**	**0.002**
SVM (water)	**0.96**	**0.07**
XGBoost (water)	**0.9993**	**0.008**
RF (gas)	**0.992**	**0.023**
MLP (ANN) (gas)	**0.997**	**0.0018**
SVM (gas)	**0.94**	**0.07**
XGBoost (gas)	**0.995**	**0.02 1**

Table- 4.1 showing results of all Algorithms used with their corresponding RMSE score, R2 score for each phase.

To compare the results of the different machine learning models discussed earlier, we compare the R2 score and RMSE to evaluate their performance. Based on the results for the test dataset, the ANN and XGBoost regression algorithms appear to be among the best after hyperparameter tuning for all.

`

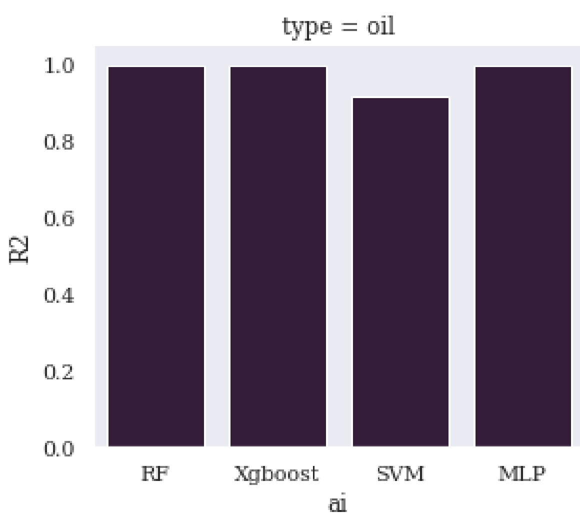
For Oil estimation:

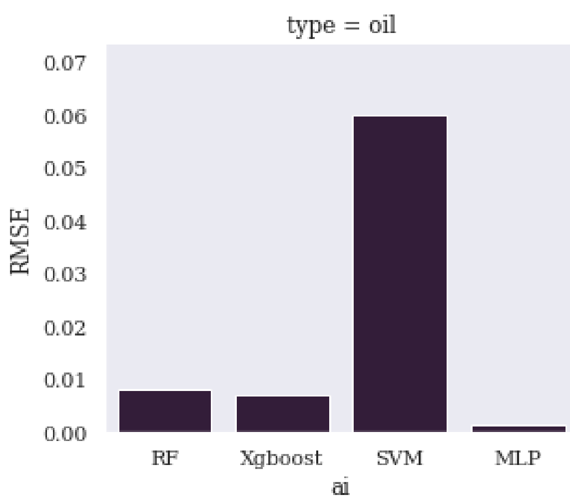
The machine learning algorithms used are:

- Random Forest (RF)
- eXtreme Gradient Boosting (Xgboost) algorithm
- Support Vector Machine (SVM)
- Artificial Neural Network (ANN) or multi layer perceptron (MLP)

Machine learning algorithms	**Test set (25%) Average R^2**	**RMSE**
RF	**0.996**	**0.008**
Xgboost	**0.997**	**0.007**
SVM	**0.92**	**0.06**
MLP	**0.998**	**0.0015**

Table- 4.2 showing results of all Algorithms used with their corresponding RMSE score, R2 score for oil flow rate estimation.





Figures 4. 26 - 4. 27 showing histograms of various AI accuracy distribution (left), Showing the RMSE error distribution among various AI for oil flow estimation.

For each ML algorithm, a total of 1000 model runs are performed and average result is shown; For each model run, 75% data is used to train the model, and 25% data is used to test the model;
In addition, hyperparameters tuning was run for each model. Moreover, MLP performs best and overcoming the overfitting problems compared to other methods.

For water estimation:

- **Machine Learning algorithms used:**
  - Random Forest (RF)
  - eXtreme Gradient Boosting (Xgboost) algorithm

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- Support Vector Machine (SVM)
- Artificial Neural Network (ANN) or multi layer perceptron (MLP)

Machine learning algorithms	Test set (25%) Average R^2	RMSE
RF	**0.9994**	**0.005**
Xgboost	**0.9993**	**0.008**
SVM	**0.96**	**0.07**
MLP	**0.997**	**0.002**

Table- 4.3 showing results of all Algorithms used with their corresponding RMSE score, R2 score for water phase estimation.

For each ML algorithm, a total of 1000 model runs are performed and average result is shown. Moreover, For each model run, 75% data is used to train the model, and 25% data is used to test the model; In addition, hyperparameters tuning was run for each model. Thus, RF performs best and overcoming the overfitting problems compared to other methods.

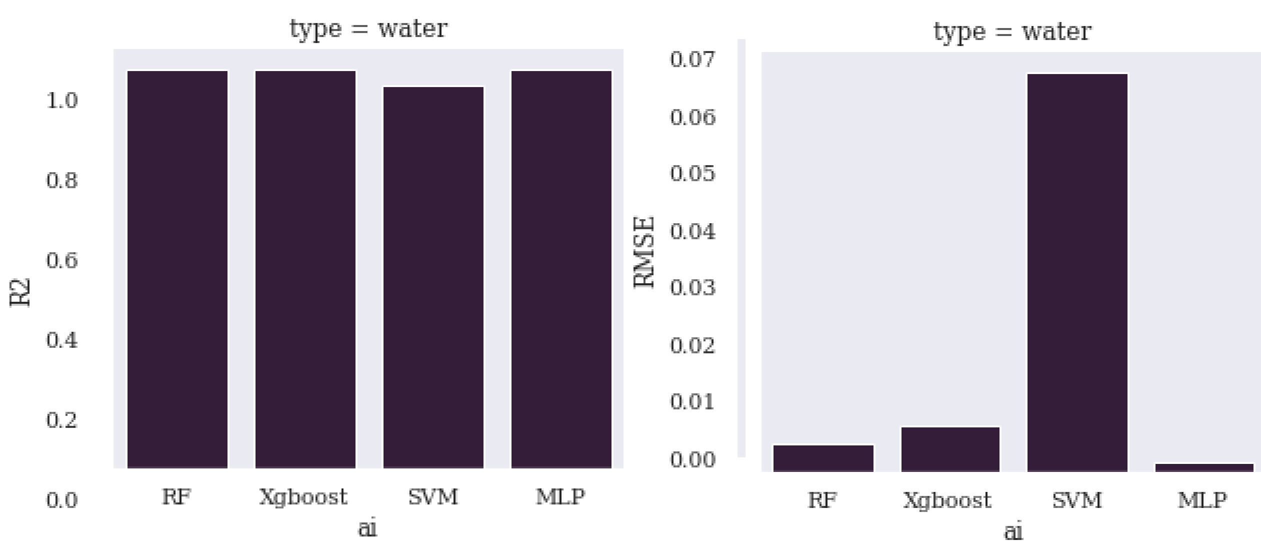


Figure 4. 28-29 showing histograms of various AI accuracy distribution (left), Showing the RMSE error distribution among various AI for water flow estimation.

For gas estimation:

- Machine Learning algorithms used:
  - Random Forest (RF)
  - eXtreme Gradient Boosting (Xgboost) algorithm
  - Support Vector Machine (SVM)
  - Artificial Neural Network (ANN) or multi layer perceptron (MLP)
-

Machine learning algorithms	Test set (25%) Average R^2	RMSE
RF	**0.992**	**0.023**
Xgboost	**0.995**	**0.021**
SVM	**0.94**	**0.07**
MLP	**0.997**	**0.0018**

Table- 4.4 showing results of all Algorithms used with their corresponding RMSE score, R2 score for gas phase estimation.

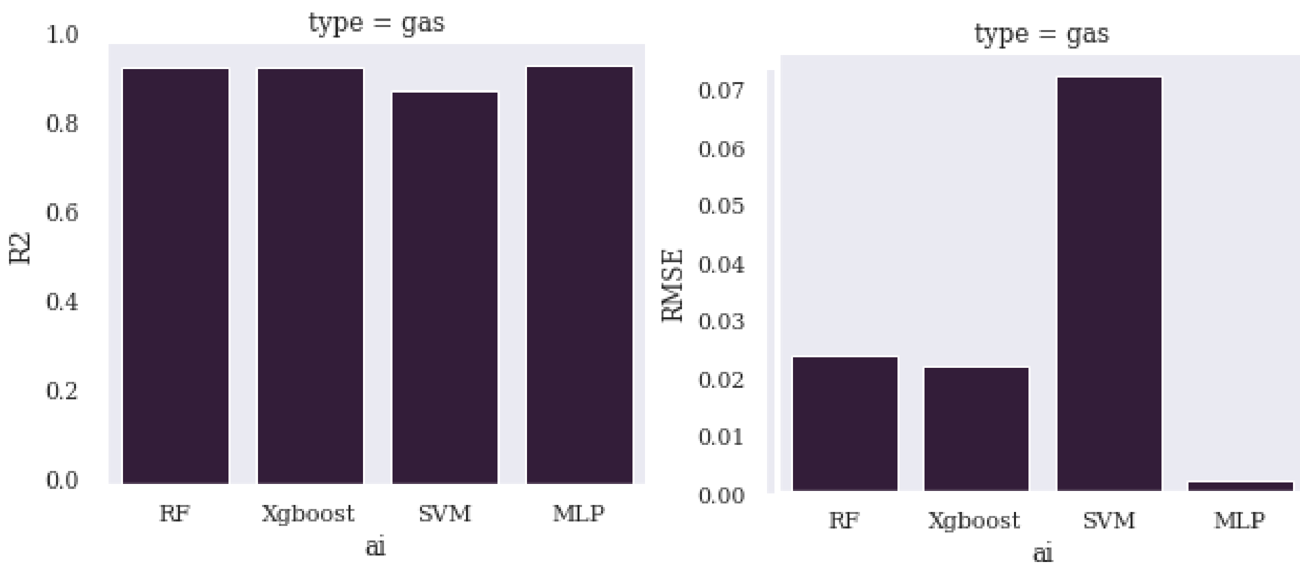


Figure 4. 30-31 showing histograms of various AI accuracy distribution (left), Showing the RMSE error distribution among various AI for gas flow rate estimation.

For each ML algorithm, a total of 1000 model runs are performed and average result is shown. Then, for each model run, 75% data is used to train the model, and 25% data is used to test the model. In addition, hyperparameters tuning was run for each model. Also, MLP performs best and overcoming the overfitting problems compared to other methods.

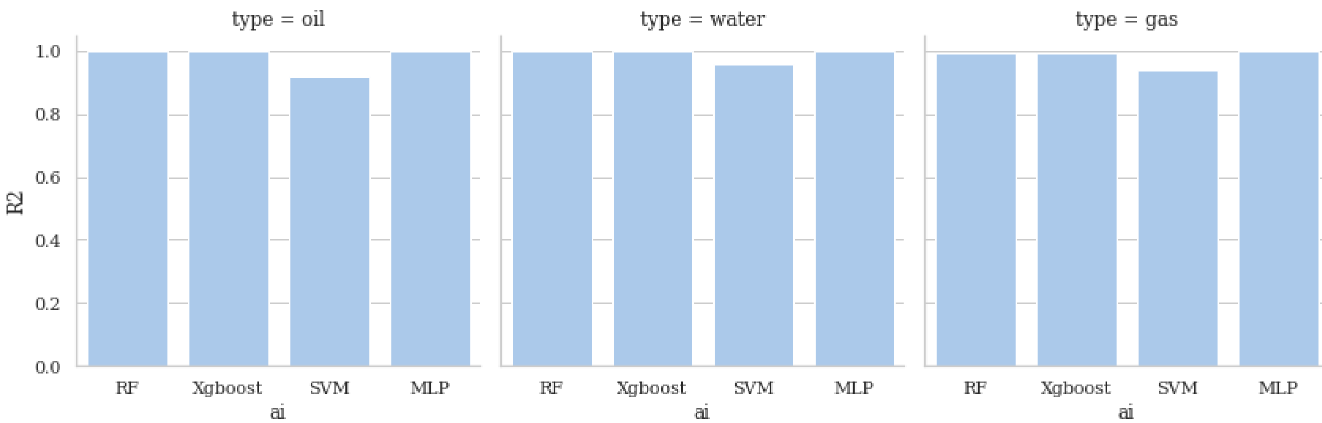


Figure 4. 32 showing histograms of various AI accuracy distribution for all phases

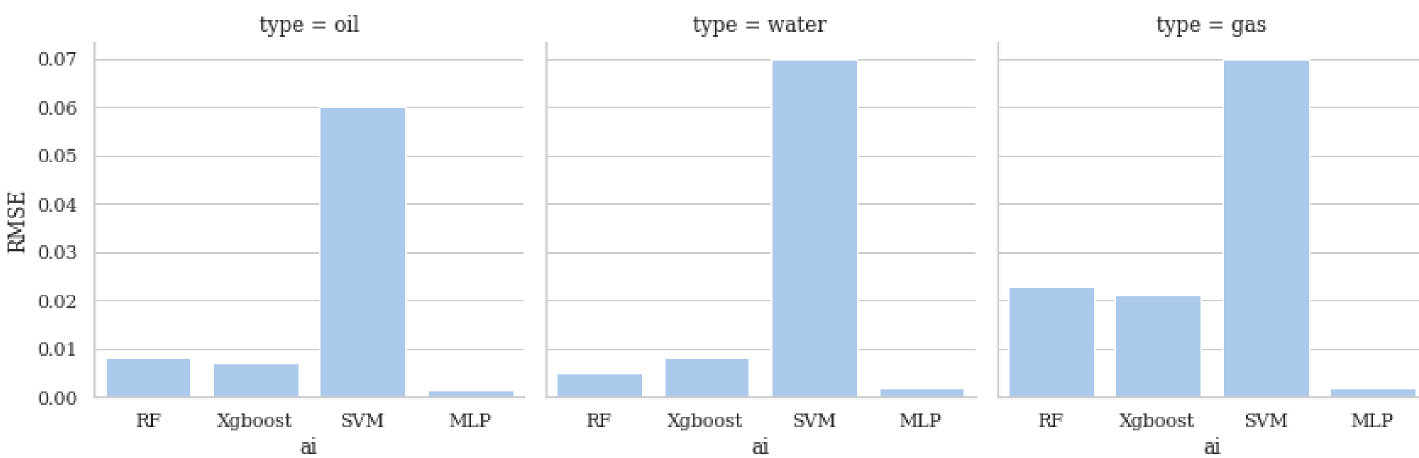
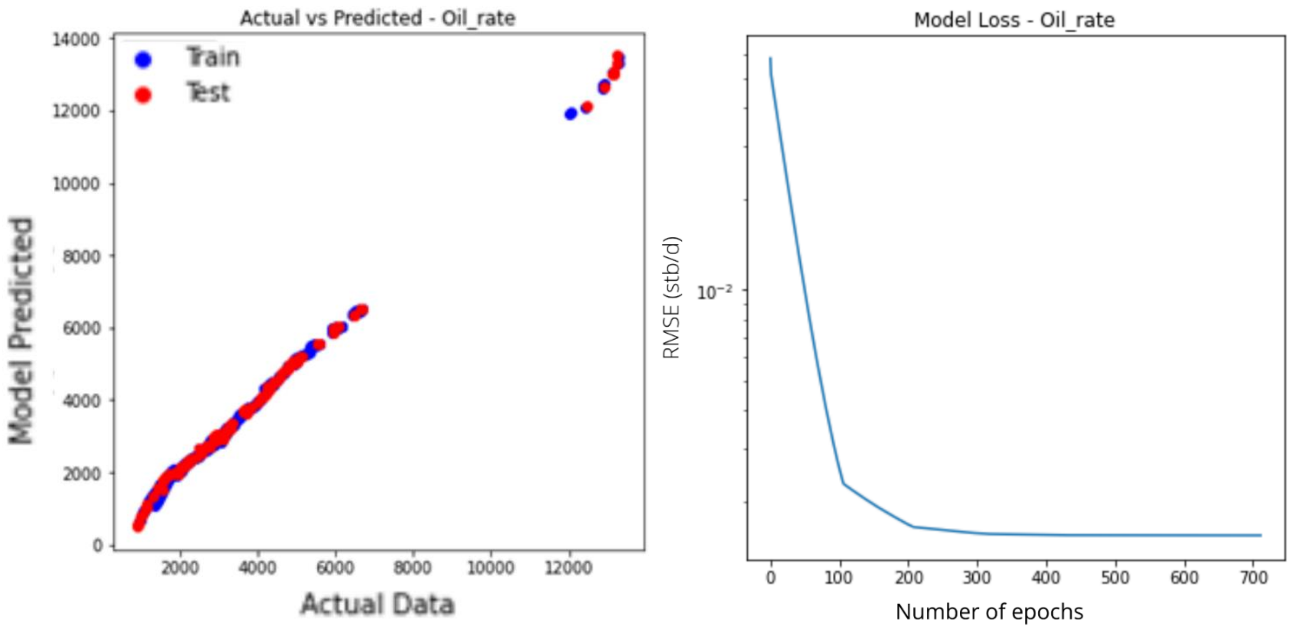
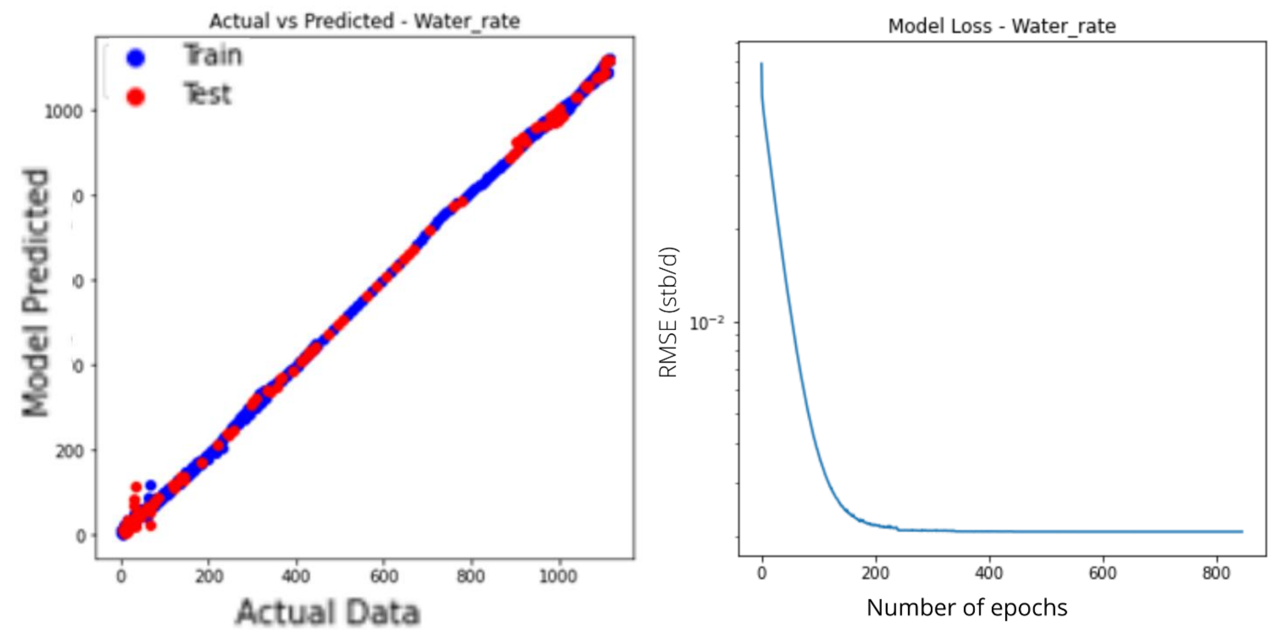


Figure 4. 33 showing histograms of RMSE error distribution among various AI for all phases



Figures 4. 34-35 showing predicted result of ANN or MLP algorithm over test data for oil(right), with its corresponding loss function graphs with respect to number of iterations(left).



Figures 4. 36-37 showing predicted result of ANN or MLP algorithm over test data for water(right), with its corresponding loss function graphs with respect to number of iterations(left).

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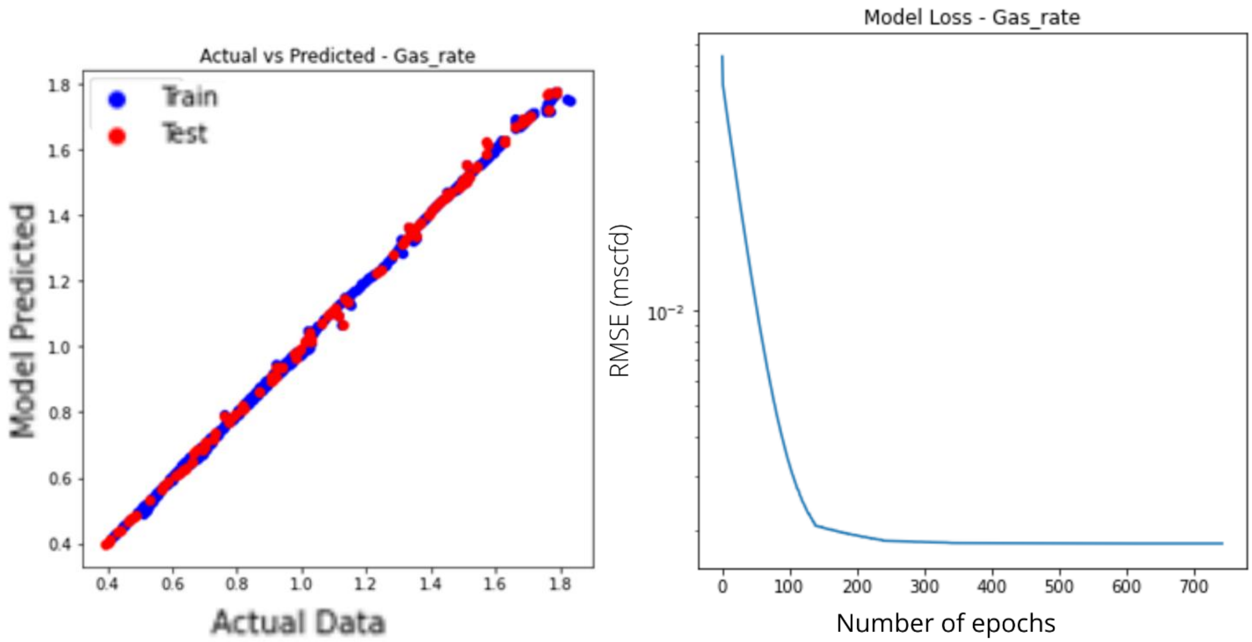

Figures 4. 38-39 showing predicted result of ANN or MLP algorithm over test data for gas(right), with its corresponding loss function graphs with respect to number of iterations(left).

In the above figures we notice that the predicted data in blue fits the tested data in all phases (oil, water and gas) over the test data where the red points are the predicted test set and the blue points represent the predicted trained set. Also, we notice that the model loss is decreasing in all 3 cases with respect to epochs. Noting that a Bayesian optimization technique was used for hyperparameters tuning. Where hyperparameters tuning consists of trying different combinations of hyperparameter and evaluating model performance.

Bayesian Optimization is a sequential approach for global optimization of black-box objective functions, that are costly to evaluate. It compromises of mathematically finding the global maximizer (or minimizer) of an unknown (black-box) objective function f:

$$\mathbf{x}^\star = \arg\max_{\mathbf{x}\in\mathcal{X}} f(\mathbf{x})$$

Where x are the hyperparameters.

Finding the function f which is unknown which could be:

- Gaussian processes
- Tree-parzen estimator
- Random Forests

1) In Bayesian optimization we treat f as a random function and place a prior over it. (the prior is a function that captures the belief -distribution, behavior-of f)
2) Then, we evaluate f at certain points.
3) With the new data, the prior (f original belief) is updated to a new the posterior distribution.
4) The posterior distribution is used to construct an acquisition function to determine the next query

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point which could be:

- Expected Improvement (EI)
- Gaussian process upper confidence bound (UCB)

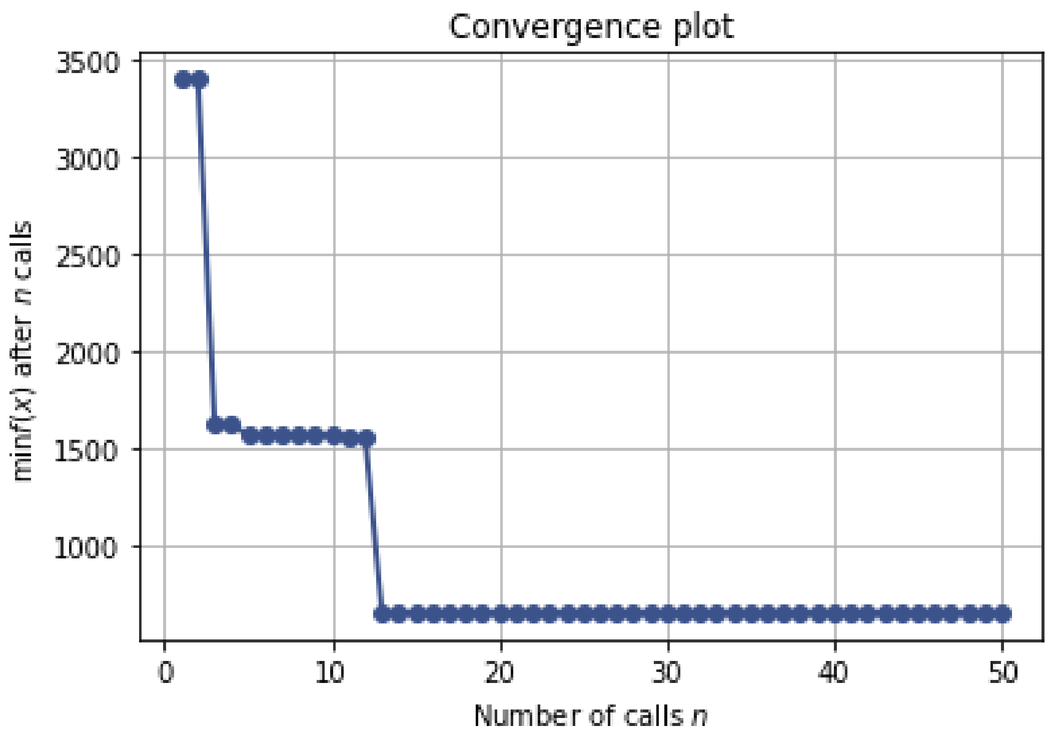

Figure 4. 40 showing hyperparameters function convergence graph at the end of hypertuning for MLP algorithm.

The figure above shows the change the optimization process of the objective function with respect to number of calls n. in which we see the objective function minimum value decrease with number of calls till becomes constant after 12 calls with a value of approximately equal to 600.

Bayesian optimization in a brief is an extremely powerful technique when the mathematical form of the objective function is unknown or expensive to compute. The main idea behind it is to compute a posterior distribution (also called surrogate function) over prior (the objective function) based on the data (using the famous Bayes theorem), and then select good points to try with respect to this posterior distribution. If we can completely match the posterior with prior, then we can precisely determine the configuration of the hyperparameters which invokes the highest return. the prior used is guassian process regression function.

While it also uses acquisition function, which does automatic trade-off between exploration when we have high uncertainty or variance) and exploitation(when we have high mean or prediction). At each iteration, the acquisition function is maximized to determine where next to sample from the objective function. The objective is then sampled at the argmax of the acquisition function, and based on the return value from the objective function, the Gaussian process is updated and this process is repeated. the acquisition function used is the probability of improvement.

4.2 Case Study 2: Root Cause analysis using Bayesian Network

4.2.1 Introduction

Technical analysis methods and diagnostics are applied to identify the reasons why performance may be above or below expectations.
The goal is to identify the constraint, such as whether fluid production is limited by reservoir pumpability,
been replaced as part of a proactive workover plan. Many of the components have a limited life, especially the seals, which wear out over time. The failure rates in each of the three stages are unrelated and must be analyzed separately.

Thus, in this case study we will discuss a Bayesian network in which we discover the potential of Bayesian networks to predict the root cause of ESP breakdown. Noting that this concept can be used to predict root cause of different patterns such as change in pressure, flow rate or other tools for diagnostics other than ESP breakdown.

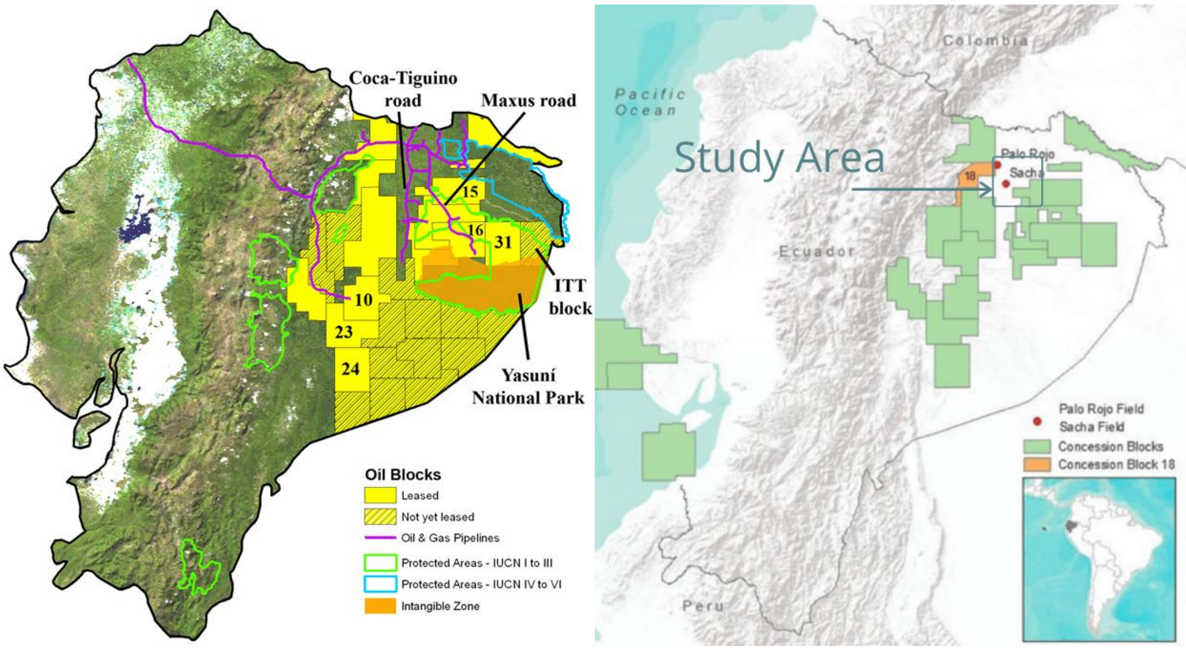

Figure 4. 41 showing location of the well where our data is from.

The algorithm used is **the constraint-based causal structure learning (PC algorithm). The goal is to calculate the presence or absence and direction of causality from the data. This is called causal search**.

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DHIntakePressure	DHDischargePressure	DHMotorTemp	DHIntakeTemp	VsdFreqOut	VsdMotAmps
435.899994	3671.699951	255.199997	229.600006	50	23.6
436.600006	3670.900146	255.400009	229.600006	50	24.1
437.200012	3670.699951	255.400009	229.800003	50	24
437.899994	3670.5	255.400009	229.800003	50	24
438.300018	3670.5	255.400009	229.800003	50	23.800001
438.800018	3669.699951	255.199997	229.800003	50	24.1
439.300018	3670.699951	255.400009	229.800003	50	23.6
439.899994	3669.5	255.199997	229.800003	50	24.200001
440.300018	3668.600098	255.400009	229.600006	50	23.9
440.800018	3670.5	255.400009	229.800003	50	24
441.5	3668.400146	255.400009	229.800003	50	24
441.700012	3668.300049	255.400009	229.800003	50	23.6
442	3669.5	255.400009	229.600006	50	24
442.200012	3669.699951	255.400009	229.800003	50	23.9
442.5	3667.800049	255.400009	229.600006	50	24
442.600006	3669.5	255.400009	229.800003	50	24.1
442.899994	3667.400146	255.400009	229.800003	50	24.200001
442.899994	3665.300049	255.400009	229.800003	50	24.5
443	3666.400146	255.400009	229.800003	50	23.800001
443.100006	3666.5	255.400009	229.800003	50	24.1
443.200012	3667	255.400009	229.800003	50	24.4
443.300018	3662.400146	255.600006	229.800003	50	24.1
443	3660.5	255.400009	229.800003	50	23.6
442.700012	3660.699951	255.400009	229.800003	50	24
442.600006	3661.600098	255.400009	229.800003	50	24.1

Table 4.5: showing data used for one pump having a stoppage.

The above table shows the data used in this example

This is done through PC algorithm:

INPUT: Vertex Set V, Conditional Independence Information
OUTPUT: Estimated skeleton C, separation sets S (only needed when directing the skeleton afterwards)
Form the complete undirected graph $\tilde{C}$ on the vertex set V.
$\ell = -1; \quad C = \tilde{C}$
repeat
  $\ell = \ell + 1$
  repeat
    Select a (new) ordered pair of nodes i, j that are adjacent in C such that $|adj(C,i) \setminus \{j\}| \geq \ell$
    repeat
      Choose (new) $\mathbf{k} \subseteq adj(C,i) \setminus \{j\}$ with $|\mathbf{k}| = \ell$.
      if i and j are conditionally independent given $\mathbf{k}$ **then**
        Delete edge i, j
        Denote this new graph by C
        Save $\mathbf{k}$ in $S(i,j)$ and $S(j,i)$
      end if
    until edge i, j is deleted or all $\mathbf{k} \subseteq adj(C,i) \setminus \{j\}$ with $|\mathbf{k}| = \ell$ have been chosen
  until all ordered pairs of adjacent variables i and j such that $|adj(C,i) \setminus \{j\}| \geq \ell$ and $\mathbf{k} \subseteq adj(C,i) \setminus \{j\}$ with $|\mathbf{k}| = \ell$ have been tested for conditional independence
until for each ordered pair of adjacent nodes i, j: $|adj(C,i) \setminus \{j\}| < \ell$.

Figure 4. 42 showing the pseudocode of PC algorithm for skeleton making

Algorithm 2 Extending the skeleton to a CPDAG

INPUT: Skeleton G_{skel}, separation sets S
OUTPUT: CPDAG G
for all pairs of nonadjacent variables i, j with common neighbour k **do**
  if $k \notin S(i,j)$ **then**
    Replace $i - k - j$ in G_{skel} by $i \rightarrow k \leftarrow j$
  end if
end for
In the resulting PDAG, try to orient as many undirected edges as possible by repeated application of the following three rules:
R1 Orient $j - k$ into $j \rightarrow k$ whenever there is an arrow $i \rightarrow j$ such that i and k are nonadjacent.
R2 Orient $i - j$ into $i \rightarrow j$ whenever there is a chain $i \rightarrow k \rightarrow j$.
R3 Orient $i - j$ into $i \rightarrow j$ whenever there are two chains $i - k \rightarrow j$ and $i - l \rightarrow j$ such that k and l are nonadjacent.
R4 Orient $i - j$ into $i \rightarrow j$ whenever there are two chains $i - k \rightarrow l$ and $k \rightarrow l \rightarrow j$ such that k and l are nonadjacent.

Figure 4. 43 showing the pseudocode of PC algorithm for edge orientation

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Noting that more explanation about the algorithm used can be found in chapter 1.

4.2.2 Results

Thus, the idea of this chapter is to show the potential of machine learning technique for downhole equipment.

In this case, we implemented the data took from real ESP working on the field which experienced breakdowns. So, in order to figure out what is the root cause of this problem, PC algorithm was used.

From first pump Sacha 460V operating in Anaconda field, using that Bayesian algorithm we were able to figure out that the change in current caused the problem while for Sacha-205D the pump was working normally but the algorithm deduced the root cause of each change.

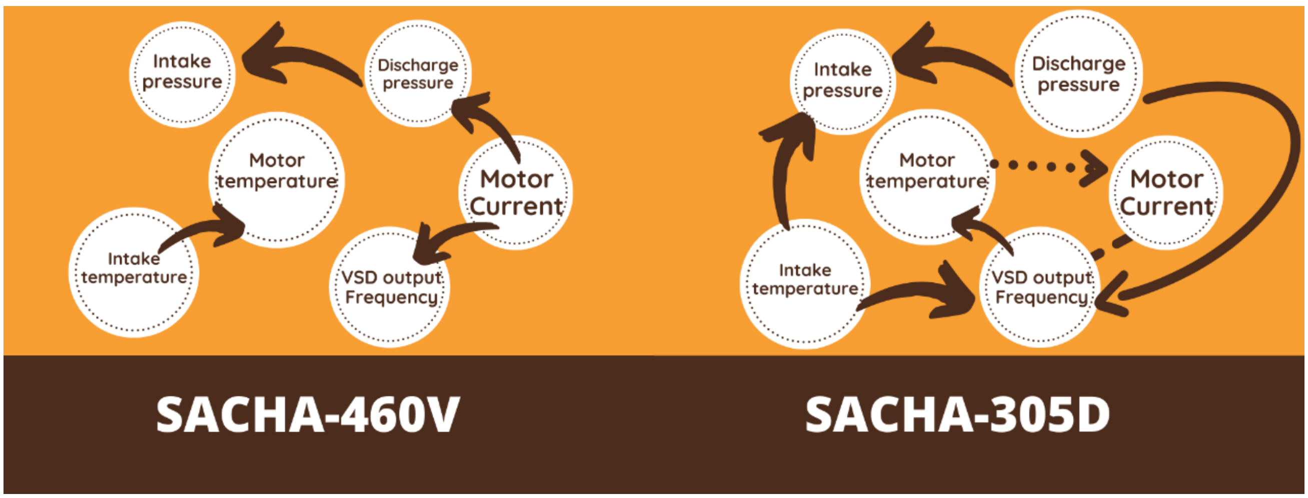

Figure 4. 44 showing the maps of root cause of events for Sacha-460V(left) and Sacha-305D(right)

Down we see what the VSD was reading on surface for both pumps.

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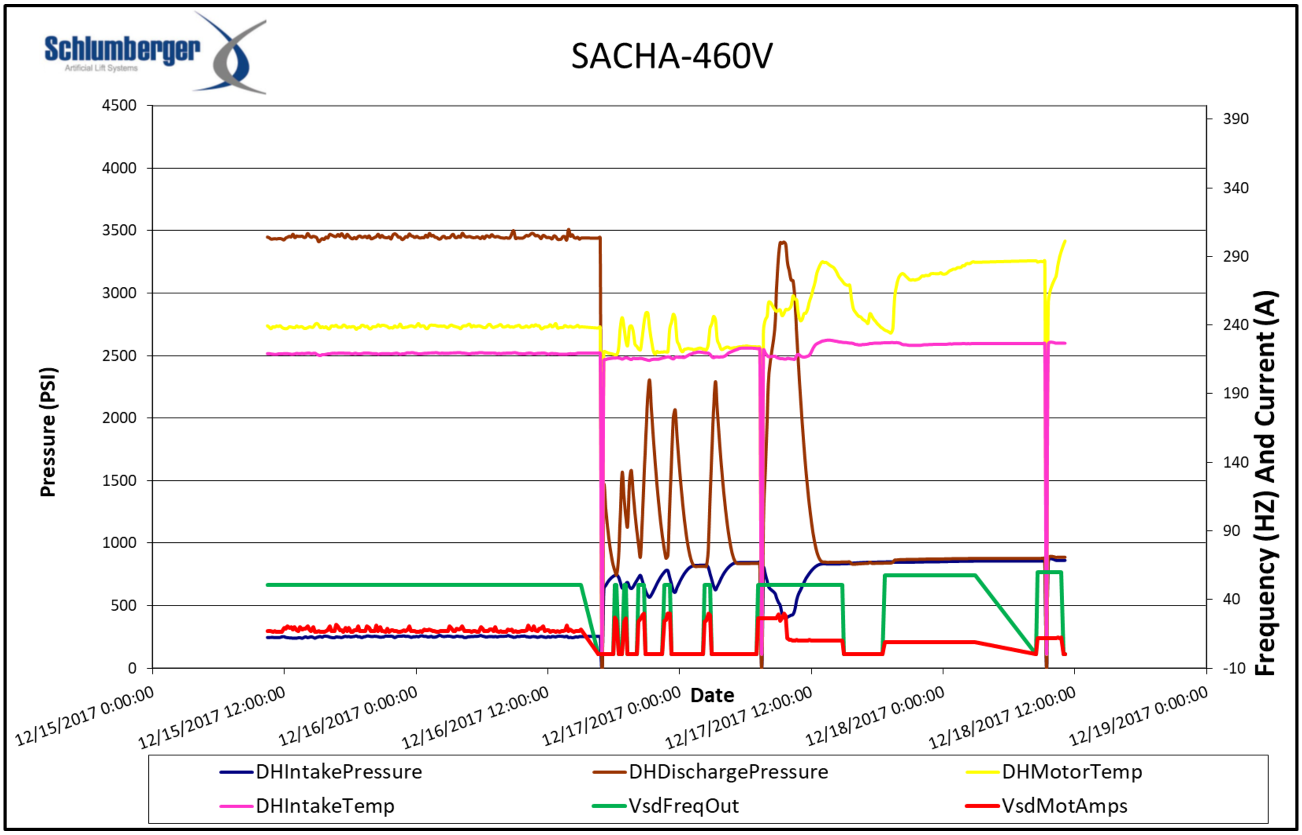

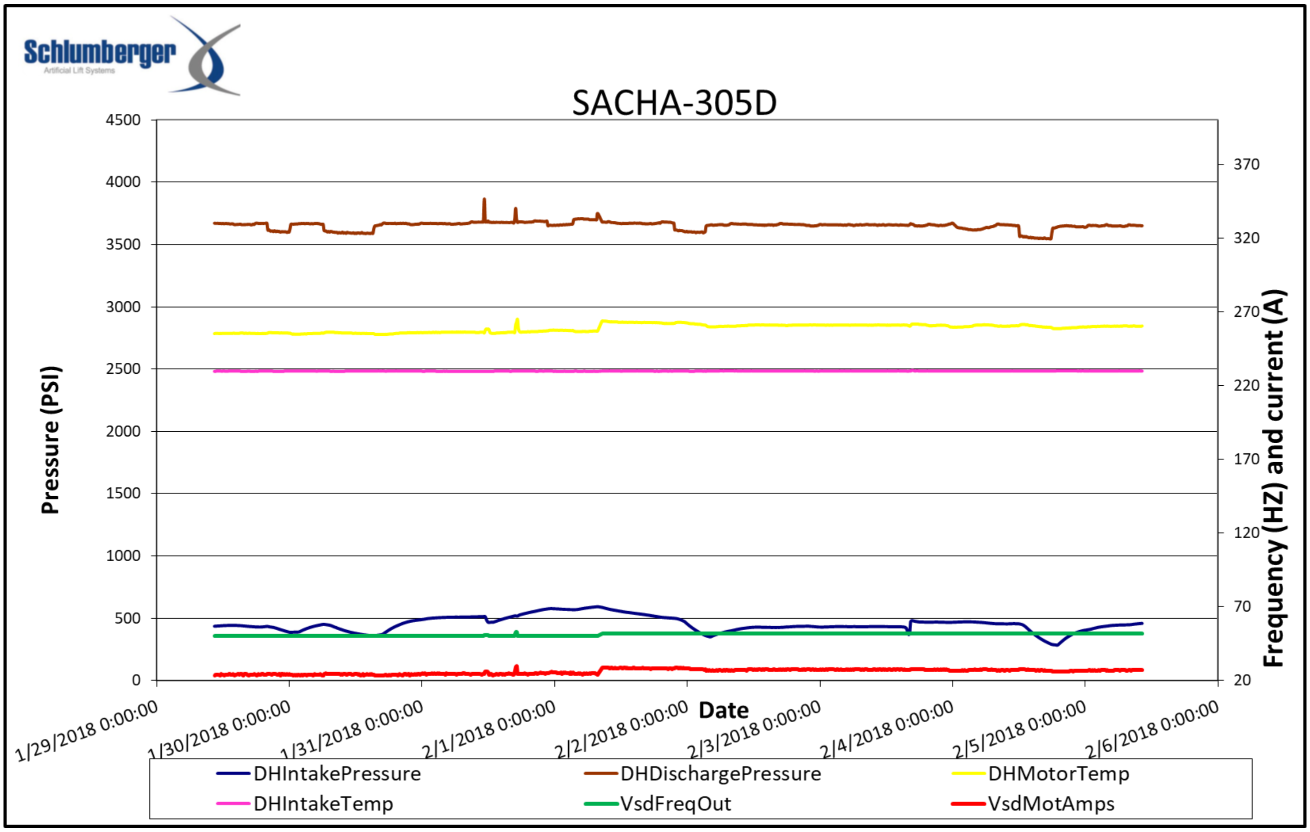

Figures 4. 45-46 showing the VSD surface readings for Sacha-460V(left) and Sacha-305D(right)

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After consulting the reports of the specialized engineers, it was recognized after stoppages by some time that the changes in Sacha-460D were due to a mechanical problem in the pump in which the change in current was indicating that problem. This means this algorithm showed its efficiency regarding predicting the root cause of the problem faced.

4.3 Case Study 3: Reinforcement learning in well injection

Another challenging and interesting subject is to study the usage of reinforcement learning in oil production. In this case study we explore the reinforcement learning algorithm and how can be implemented in oil production. Some assumptions might not 100% applicable in the field.

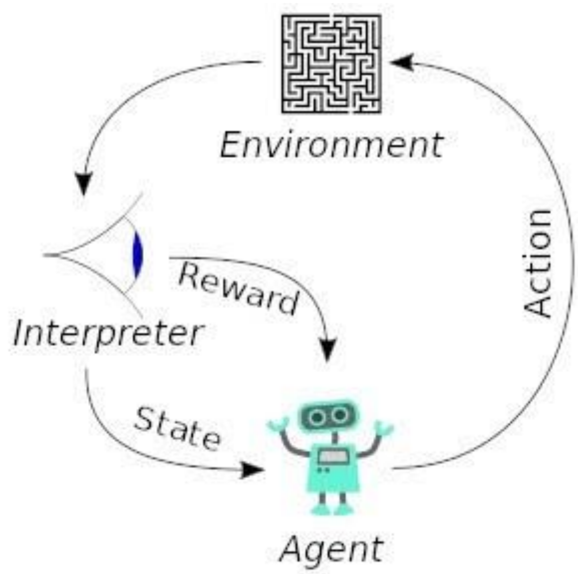

Figure 4. 47 showing the cycle of reinforcement learning

4.3.1 Problem to solve

In this case study, we will develop and test the ability of reinforcement learning to generate a model that minimize the cost of injection while keeping the reservoir pressures in its optimal pressure ranges.
We will set up our own pressure environment, and we will build an AI that will be controlling the injection mode That keeps the reservoir in its optimal range of pressure while saving the maximum energy and injected fluid. Thus, minimizing the costs. Such as DeepMind AI for Google servers did, the goal here will be to achieve the maximum energy savings.

4.3.2 Problem solution and results

Before we define the states, actions and rewards, we need to explain how the system operates. We will do that in several steps. First, we will list all the environment parameters and variables by which the well is controlled. After that we will set the essential assumption of the problem, on which our AI will rely to provide a solution. Then we will specify how we will simulate the whole process. And eventually we will explain the overall functioning of the system, and how the AI play its role.
First, a dataset of all parameters during gas lift operation is trained using Xgboost.

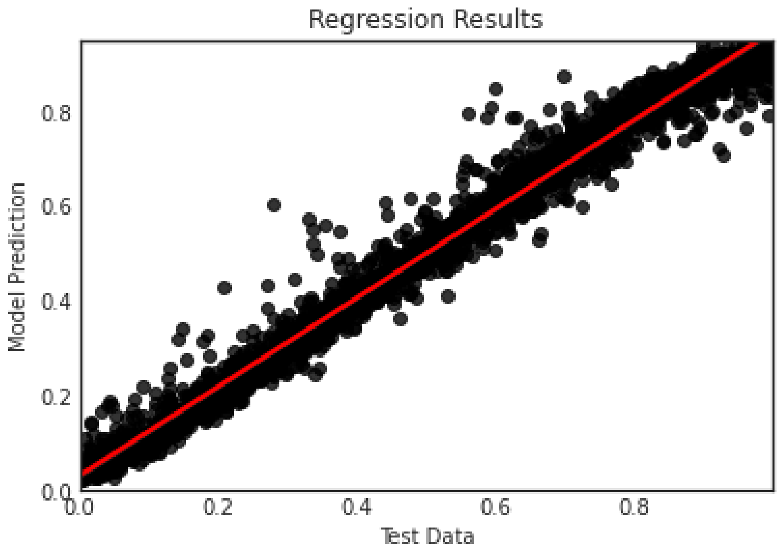

Figure 4. 48 showing the result of the predicted XgBoost model on the test data

In the above figure it shows the prediction results vs the tested data of the xgboost model used. The predicted data follow a straight line (in red) with a very small deviation from the origin with respect to the tested data.

A similar dataset of water injection can be used in order to save injected water and thus reduce operation cost. Two main functions integrated in the RL model will be taken into consideration in this thesis:
Xgboost model that predict reservoir pressure with its controlling parameters and the cost function.
Going back to the dataset given, the features are selected by importance after running performance accuracy test by predicting reservoir pressure using all the other parameters in order to reduce computing power and time. These features importance ranks are as shown per the following figure.

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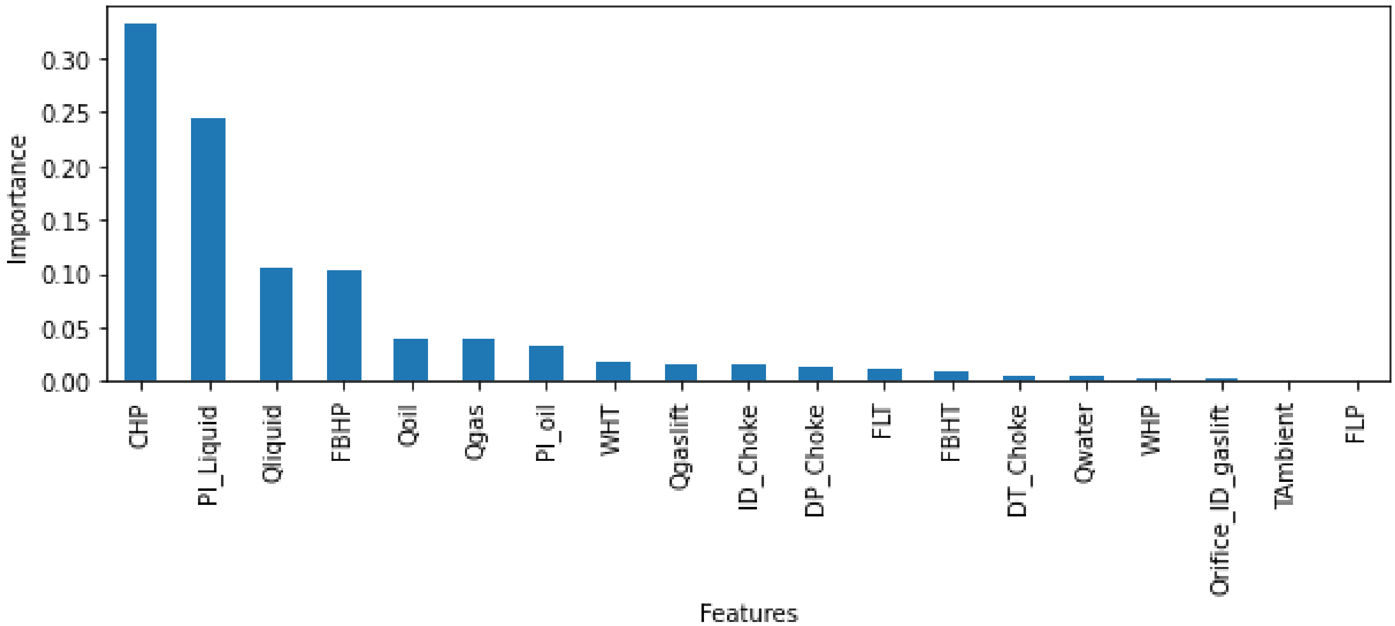

Figure 4. 49 showing the distribution of features importance on the prediction.

So in the system we have, we are dealing with a specific reservoir that its pressure controlled by different parameters and variables. Every certain period of time, our parameters changes such as PI, liquid flow rate, choke pressure. We select the first 3 parameters in our modelling.

Two possible ways can regulate the pressure in the reservoir: first, the tested AI algorithm here. Secondly the conventional injection which injects to increase the pressure when the pressure is very low. The conventional way will automatically bring back the reservoir pressure to its optimal production pressure.

Let's explain this in more details: when the reservoir pressure is updated every period of time, it can either stay within the range of optimal pressure (in this example [3800 PSI; 4000 PSI]), or go outside this range. If before it goes outside the optimal range, like say less than 3800 PSI, a conventional way system will automatically bring the pressure back to the closest bound of the optimal range, that is 3800 PSI. However, this conventional way system will do that only when the AI is not activated. If the AI is activated, then in that case the conventional way system is deactivated and it is the AI itself that updates the pressure of the reservoir to regulate it the best way. But the AI does that after some prior predictions, not in a deterministic way as with the conventional system. Before there is an update of how the liquid PI is changing, choke pressure changing and the liquid flow rate causing to change the pressure of the reservoir, the AI predicts if it should inject, do nothing. The liquid PI, choke pressure and liquid flow were assumed changing randomly within a range of values. So, after each change our model predicts the new pressure of the reservoir and predicts the action needed thus the energy cost. Then the pressure change happens and the AI reiterates. Thus, moving from pressure to energy is the goal, to save some energy spent while doing injection. Accordingly, the AI has to spend less energy than the energy spent by the conventional way. For simplicity reasons we will deal with the energy spent as how much pressure saved as the energy needed within one unit of time.

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then that means that the energy saved by the AI at each iteration t (each period of time) is in fact the difference in absolute changes of pressures caused on the reservoir between the conventional way and the AI from t and t + 1:

Steps involved:
The memory of the Experience Replay is initialized to an empty list M.
We choose a maximum size of the memory. In our case study we choose a maximum size of 100 transitions. We start in a first state, corresponding to a certain time.
At each time t, we repeat the following process, until the end of the epoch:
1. We predict the Q-Values of the current state st.
2. We play the action that corresponds to the maximum of these predicted Q-Values (argmax method):

$$a_t = \underset{a}{\operatorname{argmax}} Q(s_t, a)$$

3. We get the reward:
rt= Cost_no_ai - Cost_with_ai

4. We reach the next state st+1.
5. We append the transition (st; at; rt; st+1) in M.
6. We take a random batch B included M of transitions. For all the transitions (Sti; Ati; Rti; Sti+1) of the random batch B:
We get the predictions:

$$Q(s_{t_B}, a_{t_B})$$

We get the targets:

$$r_t + \gamma \max_a (Q(s_{t+1}, a))$$

The loss is computed between the predictions and the targets over the whole batch B:

$$\text{Loss} = \frac{1}{2}\left(r_t + \gamma \max_a (Q(s_{t+1}, a)) - Q(s_t, a_t)\right)^2 = \frac{1}{2} TD_t(s_t, a_t)^2$$

The model backpropagates the loss function back into the neural network, and using stochastic gradient descent it updates the weights according to how much they contributed to the error.

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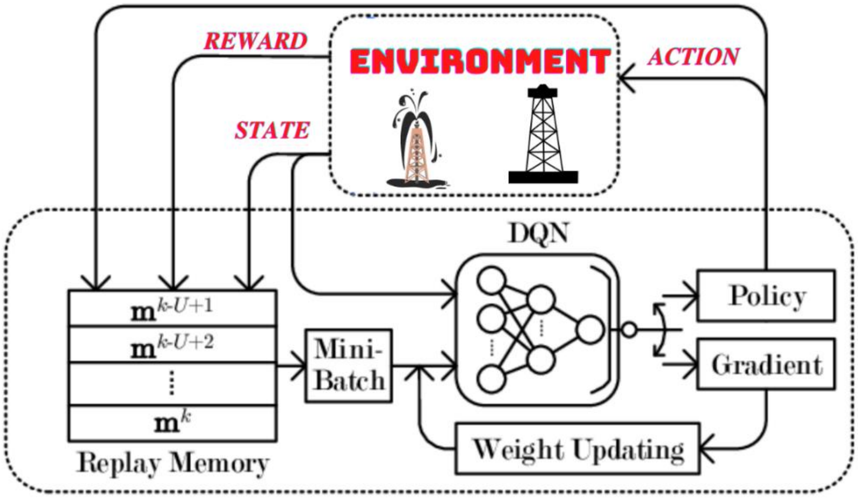

Figure 4. 50 showing the cycle of how the algorithm works

Initial points were selected from the data file provided and assuming having the following: initial choke pressure = 3477.12 PSI , initial productivity index of liquids = 10.82 ,initial liquid flow rate = 4559.82 bbl/d ,minimum choke pressure = 1000 PSI ,Maximum choke pressure = 5000 PSI, minimum reservoir pressure = 3600 PSI ,maximum reservoir pressure = 5000 PSI, minimum productivity index of liquids = 0.01 ,maximum productivity index of liquids = 590
minimum liquid flow rate = 300 bbl/d ,maximum liquid flow rate = 7000 bbl/d ,maximum updated liquid flow rate = 200 bbl/d ,maximum updated choke pressure = 70 PSI , maximum updated productivity index of liquids = 50

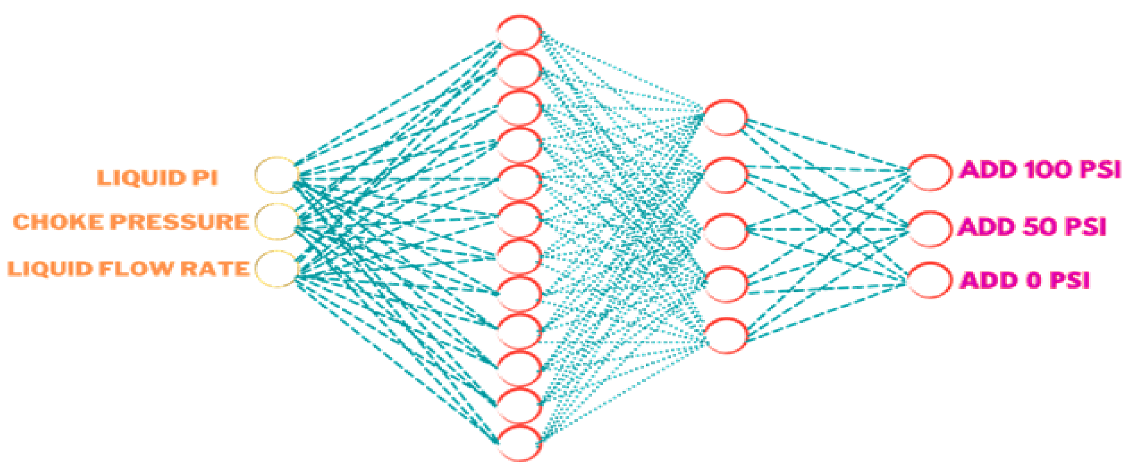

Figure 4. 51 showing the input and output of the MLP.

A random pattern of updating liquid flow rate, choke pressure and PI of liquid after each state throughout the study was selected. For each value selected a trained supervised learning algorithm (xgboost) was selected which updates the current reservoir pressure at each state. Then the model is updated as discussed before. Optimal operation pressure selected was between 4000 and 3800 PSI.

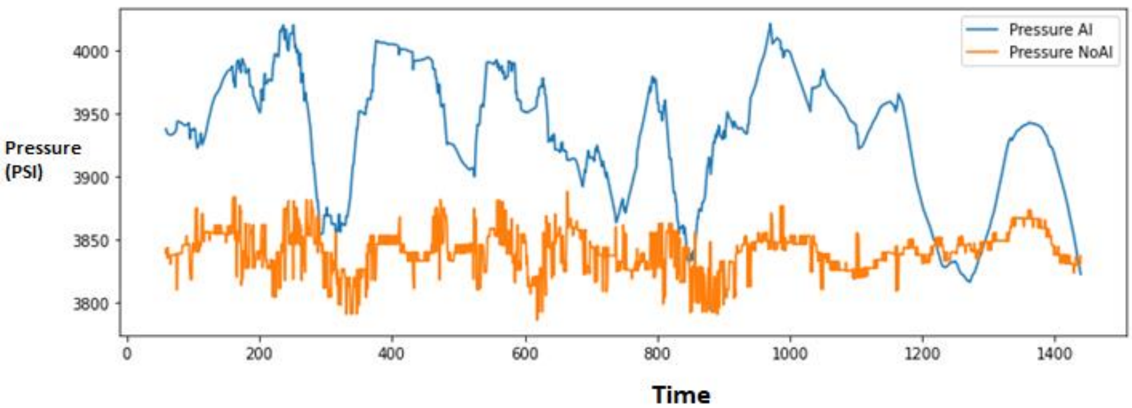

Figure 4. 52 showing pressure changes as we do injection with or without an AI agent.

The results showed an improvement of 57 % reduction. The AI decided to start injection at higher pressure from beginning and to keep injecting on a pattern different than waiting for the pressure to decrease to a threshold. Thus, this case study can be used in a further research in order to enhance the applicability of such an algorithm in more sophisticated environments.

Algorithm:

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$
  end for
end for

Figure 4. 53 showing the pseudocode of the algorithm.

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Chapter 5

5 Conclusions and future work

5.1 Conclusions

Virtual hybrid multiphase flow meter was studied for predicting the oil, water and gas flow rates from ESP readings in the first case study. Using Pipesim a python script was used for generating physics based data. These data were fed to different machine learning algorithms for virtual multiphase flow meter. Thus, given all the input variables for the model (water, ESP operating points and parameters, reservoir pressure, black oil fluid, GLR,..) each flow rate was deduced. Performing feature selection indicated that some ESP parameters plays an important role in order to predict the multiphase flow rates in an ESP system such as ESP intake pressure added to the reservoir parameters such as watercut, GLR and reservoir pressure. For oil, ESP delta pressure and temperature, ESP efficiency and pressure at the choke are the main in order to predict the oil flow rate. For gas, wellhead pressure, choke pressure with the intake volumetric flow rate of the ESP with ESP efficiency and temperature difference are the main for predicting the gas flow rate. Then after performing a hyperparameter tuning for different ML algorithms, MLP gave the best results with an accuracy of 99%.

Moreover, in a second case study, a graphical based algorithm which differs from a black box modeling such as in MLP was used. Using Bayesian Network on a dataset from different pumps in Sacha field. the change in the motor current was the root cause of an ESP breakdown was the result of the prediction. Thus, with such a model a field engineer can diagnose immediately the root cause of an ESP stoppage before dismantling the pump. While such a system can predict the root cause of the failure from the data given, an expert knowledge can be added to such a system for better diagnostics about the equipment responsible for the current change that caused the failure in the ESP. With such a model the service company can improve the equipment used in the well conditions, save time and money from diagnostics, or can be integrated with a smart system to behave autonomously in case when the root cause can be solved by a change in the operation parameters (for example in case of gas locking).

Finally, a third case study chosen using reinforcement learning. With such a model we can optimize a system with model free environments. In this case study Using data for a gas lift injection well, an agent and an environment were built where the agent tries to maximize the rewards by decreasing the operating cost for an injection well while keeping the pressure of a reservoir in its optimal ranges. The reservoir pressure change was correlated between PI liquid, Choke pressure and liquid flow rate after feature selection. The model used for updating the pressure at each state was xgboost model. Then, after combining a supervised learning model with a reinforcement learning model the RL model gave a 57% cost savings. With such a system it is enormous especially in environment where injected fluid could be hard to get or expansive. Also, that model enabled an autonomous system without the need for a human

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interference in injection.

5.2 Future Works

Our first model was based on a generated data from pipesim, while a real data can be integrated in such a model for tuning the model in the corresponding field. Another note, a problem was faced while generating data from Pipesim with the computer and software memory size which can be checked and work on it in a later study. Also, as previously mentioned an expert based knowledge can be integrated in a Bayesian network for a combination between human intelligence with artificial intelligence for solving other industry related problems such as root cause for problems faced in flow assurance. For the third case study, an improved model like twin delayed DDPG for faster computation can be used and for other different applications, tools and instruments inside the well for autonomous decision making and control. Also, the cost function can be changed from pressure to a monetary currency.

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References

[1.1] Consultancy.ai, 'Six charts on the talent gap challenge in the oil & gas sector
', November 2020, available at : https://www.consultancy.asia/news/3691/six-charts-on-the-talent-gap-challenge-in-the-oil-gas-sector
[1.2] K. Holdaway, harness oil and gas big data with analytics , Wiley
[1.3] R. A. Startzman, W. M. Brummett, J. C. Ranney, A. S. Emanuel, and
R. M. Toronyi, "Computer Combines Offshore Facilities and Reservoir Forecasts," *Petroleum Engineer*, pp. 65–76, May 1977.
[1.4] Society of Petroleum Engineers, "History of Petroleum Technology," Available at https://www.spe.org/industry/history/timeline/.
[1.5] Wikipedia, "Timeline of machine learning,". Available at https://en.wikipedia.org/wiki/Timeline_of_machine_learning.
[1.6] S. Mochizuki, L. A. Saputelli, C. S. Kabir, R. Cramer, M. Lochmann, R. Reese, L. Harms, C. Sisk, J. R. Hite, and A. Escorcia, "Real-Time Optimization: Classification and Assessment," *SPE Production & Operations,* vol. 21, no. 4, pp. SPE-90213-PA, 2006.
[1.7] L. Berendschot, K.-C. Goh, M. Stoever, R. Cramer, and S. Mehrotra, "Upstream/Downstream Real-Time Surveillance and Optimization Systems: Two Sides of the Same Coin, or Never the Twain Shall Meet," SPE Annual Technical Conference and Exhibition, San Antonio, TX, 2013.
[1.8] D. A. B. Oliveira, R. S. Ferreira, R. Silva, and E. V. Brazil, "Interpolating Seismic Data With Conditional Generative Adversarial Networks," *IEEE Geoscience and Remote Sensing Letters,* vol. 15, no. 12, pp. 1952–1956, 2018.
[1.9] G. Zangl, L. Neuhofer, D. Zabel, P. Tippel, C. Pantazescu, V. Krcmarik, L. Krenn and B. Hachmöller, "Smart and Automated Workover Candidate Selection," SPE Intelligent Energy International Conference and Exhibition, Aberdeen, Scotland, UK, 2016.
[1.10] M. Stundner, G. Zangl, L. Neuhofer, D. Zabel, P. Tippel, C. Pantazescu, V. Krcmarik, A. I. Staicu, L. Krenn, and B. Hachmöller, "Deployment of a Generic Expert System to Rank Operations Business Opportunities Automatically Under Ever-Changing Economic Conditions," SPE Annual Technical Conference and Exhibition, Dubai, UAE, 2016.
[1.11] L. Saputelli, M. Nikoalou, and M. J. Economides, "Self-Learning Reservoir Management," SPE Annual Technical Conference and Exhibition, Denver, CO, 2003.
[1.12] P. W. von Pattay, J. A. Hamer, and R. Strasser, "Unlocking the Potential of Mature Fields: An Innovative Filtering and Analysis Approach to Identify Sidetracking Candidates in Mature Water Flooded Fields," Asia Pacific Oil and Gas Conference and Exhibition, Jakarta, Indonesia, 2007.
[1.13] B. L. Williams, B. M. Weaver, and L. Weijers, "Completing the Second Target: Finding Optimal Completion Practices for the Three Forks Formation in the Williston Basin Using Multivariate Statistical Analysis," SPE Hydraulic Fracturing Technology Conference, Woodlands, TX, 2015.
[1.14] F. Miller, J. Payne, H. Melcher, J. Reagan, and L. Weijers, "The Impact of Petrophysical and Completion Parameters on Production in the Denver-Julesburg Basin," SPE Low Perm Symposium, Denver, CO, 2016.
[1.15] M. Mayerhofer, O. Oduba, K. Agarwal, H. Melcher, E. Lolon, J. Bartell, and L. Weijers, "A Cost/Benefit Review of Completion Choices in the Williston Basin Using a Hybrid Physics-Based-Modeling/Multivariate-Analysis Approach," *SPE Production & Operations,* vol. 34, no. 01, pp. 1–17, 2019.
[1.16] R. Lastra, "Achieving A 10-Year ESP Run Life," SPE Electric Submersible Pump Symposium, Woodlands, TX, 2017.

`

[1.17] R. Pragale and D. D. Shipp, “Investigation of Premature ESP Failures and Oil Field Harmonic Analysis,” *IEEE Transactions on Industry Applications*, vol. 53, no. 3, pp. 3175–3181, 2017.
[1.18] S. Gupta, L. Saputelli, and M. Nikolaou, “Applying Big Data Analytics to Detect, Diagnose, and Prevent Impending Failures in Electric Submersible Pumps,” SPE Annual Technical Conference and Exhibition,
Dubai, UAE, 2016.
[1.19] M. Abdelaziz, L. Rafael, and J. J. Xiao, “ESP Data Analytics: Predicting Failures for Improved Production Performance,” Abu Dhabi International Petroleum Exhibition & Conference, Abu Dhabi, UAE, 2017.
[1.20] T. Hastie, R. Tibshirani, and J. Friedman, “*The Elements of Statistical Learning”*, New York: Springer, 2001.
[1.21] G. James, D. Witten, T. Hastie, and R. Tibshirani, ”*An Introduction to Statistical Learning with Applications in R”*, Springer, 2013.
[1.22] Spirtes, P., Glymour, C., & Scheines, R. (2000). Causation, Prediction, and Search
[1.23] "Statistics WEB 25-5. Test of Independence" https://bellcurve.jp /statistics/course/9496.html
[1.24] Tom S. Verma, Judea Pearl. "An Algorithm for Deciding if a Set of Observed Independencies Has a Causal Explanation" https://arxiv.org/abs/1303.5435 (2013)
[1.25] "Learn while making! Causal analysis by Python" (Yutaro Ogawa, 2020)
[1.26] Felipe Schanchez “Causality and bayesian networks” available at https://towardsdatascience.com/causality-and-bayesian-networks-fcd959d4c80a
[1.27] "Introduction to effect verification" (Shota Yasui, 2020)
[1.28] “Safety-first AI for autonomous data centre cooling and industrial control”, (Chris Gamble- Jim Gao, August 2018) , https://deepmind.com/blog/article/safety-first-ai-autonomous-data-centre-cooling-and-industrial-control
[1.29] “10 Real-Life Applications of Reinforcement Learning” (Derrick Mwiti, 2021) https://neptune.ai/blog/reinforcement-learning-applications
[1.30] “Deep Reinforcement Learning: Guide to Deep Q-Learning” (Peter Foy, 2021), https://www.mlq.ai/deep-reinforcement-learning-q-learning/
[1.31] “Playing Atari with Deep Reinforcement Learning” V. Mnih, available at: https://www.cs.toronto.edu/~vmnih/docs/dqn.pdf
[1.32] Xianfu Chen “Performance Optimization in Mobile-Edge Computing via Deep Reinforcement Learning”,Researchgate,2018

[2.1] S. Breit and N. Ferrier, April 2008. “Pumps in Oil, Gas and Biofuels” [Online].
Available:http://www.woodgroup.com/SiteCollectionDocuments/news-techarticles/2008-04_ESPGainingGround_WGESP.pdf. [Accessed 15th July 2014].
[2.2] G. Takasc, “Electrical Submersible Pumps Manual - Design, Operations and Maintenance”, Elsevier Inc, 2009. ISBN 978-1-85617-557-9
[2.3] Michael Golan and Cutis H. Whitson, Well Performance, Prentice-Hall Inc.,
1985.
[2.4] Gabor Takacs, Gas Lift Manual, PennWell Corporation, 2005.
[2.5] Dake, L., Fundamentals of Reservoir Engineering, Elsvevier Science B.V,
2002.
[2.6] Clegg, J.D., editor. Production Operations Handbook. SPE, USA. 2007.
[2.7] Lloyd R. Heinze, Herald W. Winkler, James F. Lea, Decision Tree for Selection of Artificial Lift Method, SPE 29510, 1996.

`

[2.8] Jadid, M.B., Lyngholm, A., Opsal, M., Vasper, A., The Pressure's On: Innovations in Gas Lift, 2006, Volume 18.
[2.9] Basic artificial lift, Canadian Oilwell Systems Company Ltd, available at: http://www.coscoesp.com
[3.1] Baker Hughes Oil Tools, Gas Lift catalog, available at: http://www.bakerhughes.com
[3.2] Schlumberger oil tools catalog, available at:
https://www.slb.com/-/media/files/al/catalog/artificial-lift-esp-technology-catalog.ashx
[3.3] Fleshman, R., Harryson, O.L., Artificial Lift for High-Volume production, Oilfield Review, spring 1999.
[3.4] G. Takasc, "Electrical Submersible Pumps Manual - Design, Operations and Maintenance", Elsevier Inc, 2009. ISBN 978-1-85617-557-9
[3.5] H. Melbø, S. Morud, B. Bringedal, R. van der Geest and K. Stenersen, "Software that Enables Flow Metering of Well Rates with Long Tiebacks and With Limited or Inaccurate Instrumentation," Offshore
Technology Conference, Houston, TX, 2003.
[3.6] American Petroleum Institute, API Recommended Practice 86:
Recommended Practice for Measurement of Multiphase Flow, Washington, DC, 2005.
[3.7] A. Petukov, L. Saputelli, J. Hermann, A. Traxler, K. Boles, O. Nnaji, B. Vrielynck, and D. Vegunopal, "Virtual Metering System Application in the Ceiba Field, Offshore Equatorial Guinea," SPE Digital Energy
Conference and Exhibition, The Woodlands, TX, 2011.
[3.8] H. Melbø, B. Bringedal, N. Hall, S. Morud, E. Birkemoe, and C. Smith, "Uncertainty Based Allocation Using Virtual Multiphase Flow Metering," 22nd North Sea Flow Measurement, St. Andrews, Scotland, 2004.
[4.1] Grand view research,'Artificial Lift Systems Market Size, Share & Trends Analysis Report By Product' (May,2017), available at: https://www.grandviewresearch.com/industry-analysis/artificial-lift-systems-market
[4.2] Pipesim user guide version 2017.2
[4.3] pipesim 2017 python toolkit user guide
[4.4] J. Brownlee, "What is the Difference Between Test and Validation Datasets?," July 2017 available at https://machinelearningmastery.com/difference-test-validation-datasets/.