



OG21

MACHINE LEARNING IN THE PETROLEUM INDUSTRY

Report

Rev: 01

Date: November 3rd, 2020

Background and purpose

Oil and gas are likely to continue to play an important role in the global energy mix in the decades to come, but the long-term demand is increasingly uncertain due to factors such as substitution with renewables, technology shifts at the consumer end and increased costs (financial and reputational) of GHG-emissions.

The future attractiveness and competitiveness of the Norwegian petroleum sector is dependent upon:

- Low cost to be robust to potentially lower average prices than historically.
- World class safety and environmental performance to meet stakeholder expectations and industry targets.
- Shorter lead-times to attract investments.

A broad set of technologies is needed to improve the NCS competitiveness. Digital technologies are integral to most of these, and Artificial Intelligence, including its subset of Machine Learning, is increasingly becoming an important element also in the petroleum industry.

The main objective of this study has been to describe how Machine Learning could improve value creation and reduce emissions on the Norwegian Continental Shelf (NCS). The project team was challenged to answer three key questions:

1. How big is the opportunity related to ML on the NCS in terms of increased volumes, reduced costs and reduced environmental footprint?
2. To which extent is the Norwegian petroleum industry currently capable of developing and deploying ML to improve value?
3. How could ML be developed and adopted faster on the NCS?

Conclusions

- Machine Learning is transformative and requires technology leadership, full exploitation of the data and new processes and skills.
- The use of ML within the Norwegian oil and gas industry is in its infancy, characterized with many pilot initiatives. Few of these have been scaled and put into active use.
- Significant opportunities have been identified within all disciplines, in particular related to reduced GHG, reduced well delivery time, reduced OPEX, added volumes and accelerated production.
- The Norwegian oil & gas industry would have to step up its efforts significantly to fully seize this ML opportunity and release its potential. The industry capitalizes on a very small fraction of the value of the vast amount of data available for use.
- ML is part of the toolbox – choose the right tool for the task, but recognize in technology application strategies that AI/ML quality improves rapidly.

ML success require maturity in 3 areas



Organizational capability

- Culture and leadership
- Competence and skills at all levels
- Collaboration
- Changes to business models & work processes



Data

- Sufficient and relevant data
- Readable formats
- Without flaws and hidden assumptions
- Efficient data preparation and processing



Technology

- Sufficient computational power at reasonable cost
- Trusted algorithms / models
- IT platform and architecture that enable efficient scaling

OG21 Recommendations

#1 – Executive level technology leadership

#2 - Strengthen end user ML competency and awareness

#3 - Collaboration on data interoperability

#4 - Ensure mechanisms for trusted validation and QA of ML solutions

#5 - Collaboration on ML solutions and data management in selected areas

#6 - Share lessons learned

Further detailed in the report

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About OG21

OG21 has its mandate from the Norwegian Ministry of Petroleum and Energy (MPE). The purpose of OG21 is to “contribute to efficient and environmentally friendly value creation from the Norwegian oil and gas resources through a coordinated engagement of the Norwegian petroleum cluster within education, research, development, demonstration and commercialization. OG21 will inspire the development and use of better skills and technology”.

OG21 brings together oil companies, universities, research institutes, suppliers, regulators and public bodies to develop a national petroleum technology strategy for Norway.

Based on its mandate from the Norwegian Ministry of Petroleum and Energy, OG21 develops and maintains the technology strategy for the Norwegian petroleum industry.

About the project

Machine learning (ML) is widely applied in various industries and in the society, and ML is increasingly becoming an important element also in the petroleum industry.

The main objective of the study has been to describe how Machine Learning could improve value creation and reduce emissions on the Norwegian Continental Shelf (NCS).

The project team was challenged to answer three key questions:

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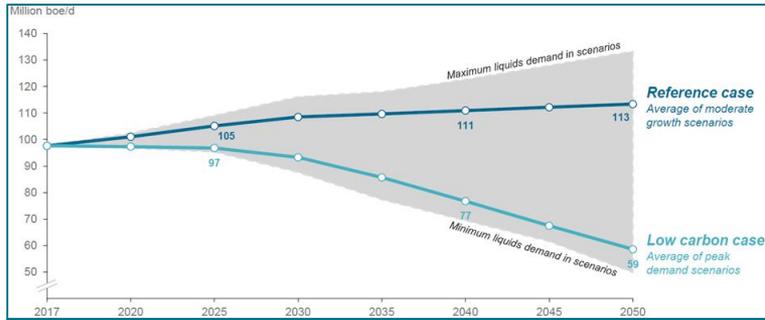
About the DNV GL report

The OG21-project included the commission of a study from DNV GL. The DNV GL report is available on the OG21 website.

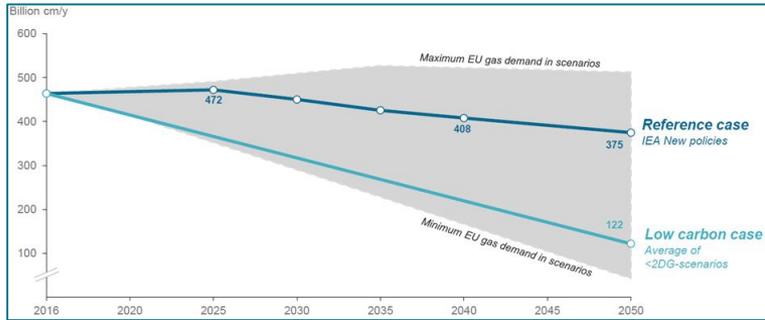
The report from DNV GL is based on in-depth interviews with stakeholders in the Norwegian petroleum industry, literature studies, in-house research and results from several OG21 workshops conducted as part of this OG21-project.

The DNV GL report is the main basis for the OG21 report. Where other sources of information have been used, these are referred to in the standard scientific reference notation.

Uncertain long-term demand – NCS producers need to be prepared for low prices and competition for market shares



Global oil demand scenarios, (OG21, 2019) (Rystad Energy, 2019)



European gas demand scenarios, (OG21, 2019) (Rystad Energy, 2019)

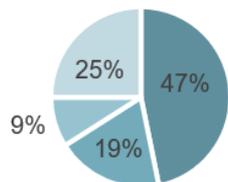
Oil and gas are likely to continue to play an important role in the global energy mix in the decades to come, but the long-term demand is increasingly uncertain. Figure 1 shows the large span of liquid demand scenarios from recognized sources such as IEA, DNV GL, Equinor, BP and OPEC, especially after 2030 (Rystad Energy, 2019).

The “low carbon” case reflects major technological and investment shifts both on the energy supply and demand side. For instance, large scale electrification of road transportation could alone address 44% of today’s oil demand (26% of the 2017 oil production was used for light vehicles and buses and 18% was used for light and heavy trucks). Simultaneously as CO₂-emissions are to be cut, efforts to improve efficiency and reduce costs need to continue in order to maintain the competitiveness of the NCS.

More than 95% of Norway’s gas production is piped to the European market, with the remainder shipped as LNG to other markets. The European market is therefore of key importance for the evacuation of natural gas from the NCS.

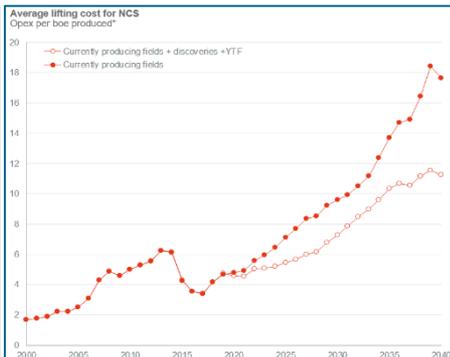
Most scenarios show robust demand for natural gas in Europe near-term and until year 2030. The use of natural gas in modern gas power plants results in only half the CO₂-emissions from coal-fired power plants, and as such natural gas is an important energy carrier to reduce European emissions on the short to medium term. After 2030 the spread is large between scenarios for European natural gas demand, ranging from remaining on today’s level towards 2050, to levels which are less than 10% of today’s demand in 2050. The EU Green Deal which puts forward a zero-emission vision by 2050, seems likely to be adopted by EU, and in this scenario, natural gas, at least without carbon capture and storage (CCS), plays a limited role.

Lots of resources left on the NCS, but NCS competitiveness depends on low cost, low emissions and short lead times



- Produced
- Reserves
- Contingent resources
- Undiscovered resources

Less than half of NCS resources produced, (NPD, 2020)



Average lifting costs per bbl increases as production declines, (Rystad Energy, 2020)

Even though the NCS is maturing, less than 50% of the potential economically viable resources have been produced (NPD, 2020).

As the production declines from a maturing NCS, the relative lifting costs per barrel increases. If we're following the current trend, lifting costs per barrel will be doubled by 2030. If that occurs, we will shift our position from being among the most cost-efficient producing regions globally, to become one of the highest cost producers (Rystad Energy, 2019).

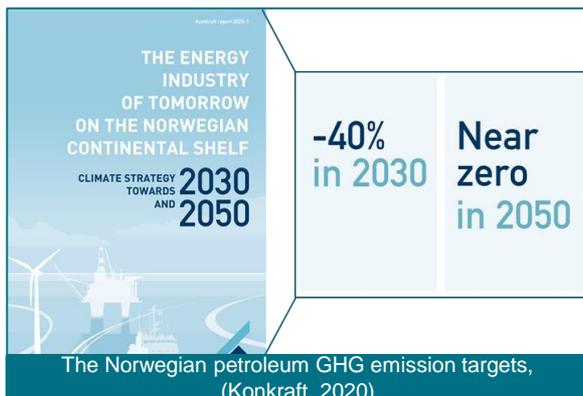
A unified oil industry in Norway have put forward very challenging CO₂-emission reductions goals: 40% reduction by 2030, and near zero in 2050 (Konkraft, 2020). The recent agreement in the Parliament on temporary tax adjustments further strengthens the climate ambitions - it calls for a plan to reduce CO₂-emissions by 50% by 2030 as compared to the 2005-level.

Institutional investors as well are increasingly demanding lower CO₂-emissions. Examples are many: several UNEP Finance initiatives subscribed to by leading banks and insurance companies; shareholder resolutions by pension funds; and statements by the world's largest asset management company, BlackRock.

Average lead times from investment decisions to production start up are higher than for onshore provinces, where especially shale oil in the US stand out with much lower lead times.

The future attractiveness and competitiveness of the Norwegian petroleum sector is thus dependent upon:

- Low cost to be robust to potentially lower average prices than historically.
- World class safety and environmental performance to meet stakeholder expectations and industry targets.
- Shorter lead-times to attract investments.



A broad set of technologies needed to improve NCS competitiveness – Machine Learning is integral to many

	TTA 1	TTA 2	TTA 3	TTA 4
Focus	Floating Offshore wind for offshore facilities Optimized gas turbines Energy effective IOR technologies Power from shore technologies Compact CCS for topsides	Water diversion Field and production optimization Cost efficient collection and processing of high quality data Big data exploration analytics CO2 for EOR	Wired pipe technologies Slot recovery technologies Automated drilling control Smarter smart wells Standardized subsea satellites	Predictive maintenance Unmanned platforms Carbon efficient supply of power and heating All electric subsea Flow assurance for long tie-ins
Other technologies	Methane sensors and cold venting Technologies for produced water and cleaning Oil spill technologies Improved regulatory and faster start-up of wells Energy efficiency sensory and digitalization software FIA technologies Combine heat and power Hybrid technologies for MODUs Barents – no pipeline technologies Gas to wire Lower production pressure in inlets Fuel cell technologies Subsea gas power generation Subsea processing technologies Technologies to reduce slugging Cooling and pressure drop in flowlines	EOR: surfactants Dry gas recovery Subsea processing technologies New completions designs Multilateral technologies Electrification of subsea wells Passive seismic and surveillance Life extension enabling technologies	Automated planning and execution in drilling Energy recovery in the draw works Hybrid technologies for MODUs Steerable liner drilling Connected wells Offshore cuttings processing on MODUs Coiled tubing drilling Data sharing systems MPD on floaters Rig less subsea intervention Thru-tubing rotary drilling	Water treatment technologies Lighthiught platforms Alternative solutions to long tie-backs CCS technologies EOR-CO2 Wet gas dehydration Life-time extension technologies

Technologies* important for NCS competitiveness, (OG21, 2019)



ML works in concert with other technologies, (DNV GL, 2020)

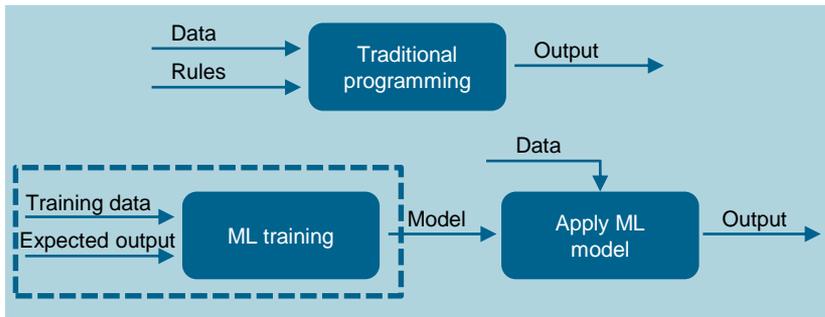
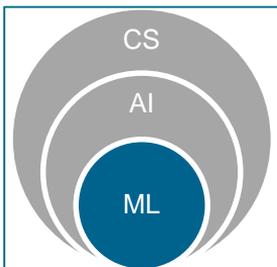
Technology priorities in the OG21 Strategy were re-visited as part of an OG21-study on “Technologies for cost and energy efficiency” in 2019. The technology needs identified in the study largely confirmed the technology prioritizations of the OG21 Strategy. Many, if not most, of the OG21 prioritized technologies contain elements of *digitalization*. And the digitalization could in many cases include machine learning, e.g. in “big data exploration”, “automated drilling control” and “predictive maintenance”

The DNV GL report confirms this: in most of the cases explored by DNV GL, ML was used in combination with other digital and non-digital technologies.

* TTAs – Technology Target Area groups:

- TTA1 – Energy efficiency and environment
- TTA2 – Exploration and improved recovery
- TTA3 – Drilling, completions and intervention
- TTA4 – Production, processing and transport

Machine learning unlocks value from sets of data, but data gathering and data management is cumbersome



Machine learning is a subset of artificial intelligence (AI) which again is a subset of computer science (CS). It uses statistical methods (algorithms) to recognize patterns in large datasets.

ML differs from traditional programming in that in contrast to known rules, the ML-model is developed from a training data set and expected outputs. The model is then applied to real data, resulting in output that is used in decision making.

Data is at the center of machine learning, but despite the increasingly vast amounts of data being gathered in society and industries, data management is not trivial, e.g.:

- Required data may be scarce or non-existent or hidden
- Data may be at wrong format and not readable for computers
- Data may contain flaws, traps or biases

For such reasons, the preparation of data could typically require 80% of the time for an ML-project (Economist/Cognilytica, 2020).

The data management issues creates opportunities for some: A new 3rd party data preparation and labelling market is emerging which could take away some of the data management burden for companies wanting to apply ML.

More complex than it looks

Average time allocated to machine-learning project tasks
January 2020, % of total

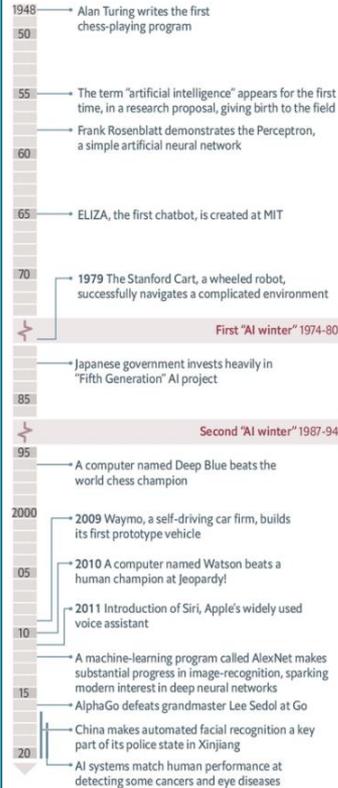


Source: Cognilytica
The Economist

Machine learning has gone through several hype cycles – this time conditions for success look more favorable

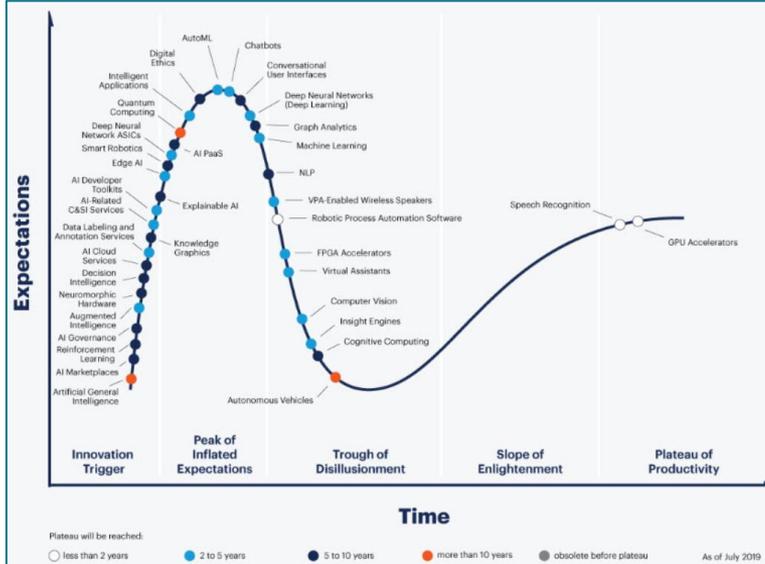
The new revolution

Artificial intelligence, selected events



Source: *The Economist*

The Economist



Gartner hype cycle for artificial intelligence 2019.

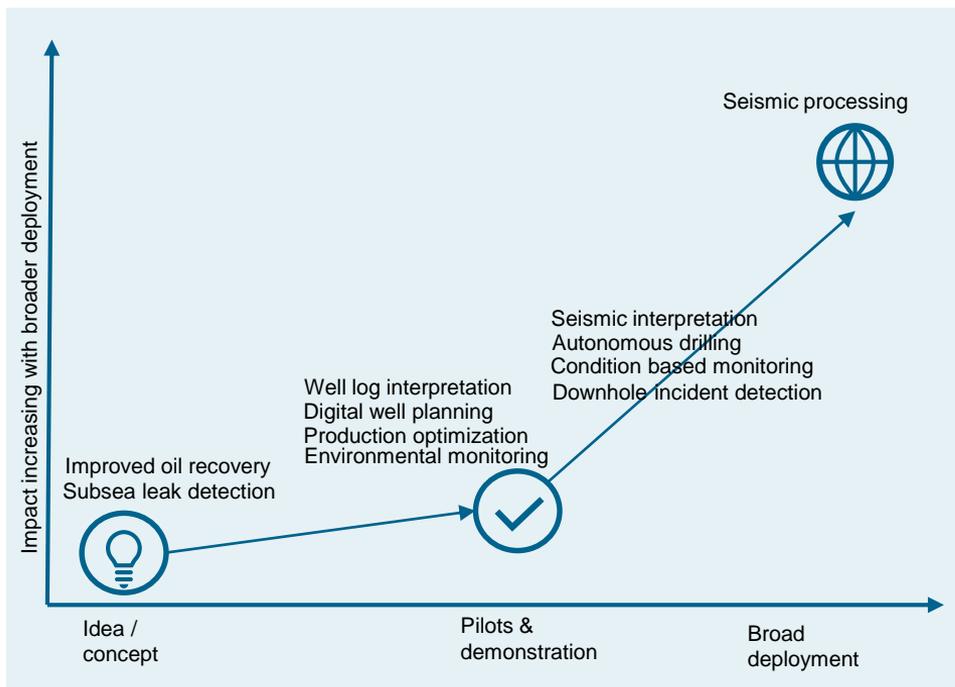
Machine learning has gone through several hypes since its inception more than 50 years ago.

According to Gartner there seems to be a hype also these days around different AI-solutions, including ML and deep neural networks (a subset of ML). The Gartner AI hype curve of 2019 is confirmed by a PWC-study of 2020 reporting a sharp decline from 2019 to 2020 in plans among business managers to apply AI (Economist, 2020).

Still, this time conditions look a lot better for harvesting benefits as compared to earlier decades' ML hypes:

- Higher computational power (but costly)
- Better algorithms (but ML is still less good at what people excel at, e.g. reasoning)
- More data (but often not relevant, or at wrong format or with flaws)

ML is already in use on the NCS – the most mature applications currently in areas with accessible, large datasets



Some examples of high potential ML applications on the NCS and their current maturity level

DNV GL has gathered information on the current status on ML use within various disciplines (DNV GL, 2020). Generally, the use of ML within the Norwegian oil and gas industry is in its infancy, characterized with many pilot initiatives. Few of these have been scaled and put into broad use.

The current maturity status on some example technologies is shown in the graph to the left.

The graph illustrates that the most mature and widely applied ML solutions are within subsurface understanding (seismic processing), an area where oil companies sits on huge amounts of in-house data.

To harvest the ML potential, the ML applications need to be matured from concepts and pilots to the broad deployment phase. Access to relevant datasets is one among many challenges on the path to broad deployment, as discussed on page 14.

IDC (2020) describes the importance of building a stepwise AI strategy:

- In the beginning the emphasis should be on building trust and demonstrate business value by prioritizing use cases with little need for horizontal integration across functions.
- Then, solutions should be multiplied and executed repeatedly.
- Eventually, the business reaches a maturity level where work processes and technology ecosystems are continuously disrupted.

ML could save costs and emissions on the NCS, in addition to adding volumes

Opportunity examples:

Potential on the NCS (DNVGL, 2020)



Energy efficiency

Optimized production w/ assumption of 7% reduced GHG emission -> 0.9 mm tons CO₂-eq./yr



Leak detection

Faster detection, more efficient oil spill response



Faster and improved seismic processing

Better decisions -> more discoveries, Assumption 1 discovery of 5 mm Sm³ o.e /yr.



Faster and improved reservoir model update

Reduced time & manning estimate of 200 mmNOK/yr, 50% success probability -> Opex savings: ~100 mmNOK /yr.



Drilling automation

Assumed 20% reduced time, 20% reduced sidetracks, 80% success probability -> Reduced drilling cost: 3-4 bn NOK/yr.



Production optimization

Well optimization and adaptive control -> Assumed 5% accelerated production, 60% success probability -> Accelerated prod. ~6 mmSm³/yr.

DNV GL has estimated significant opportunities for ML solutions on the NCS for reducing emissions and costs, increasing volumes and accelerating production. Some of the examples shown to the left (DNV GL, 2020).

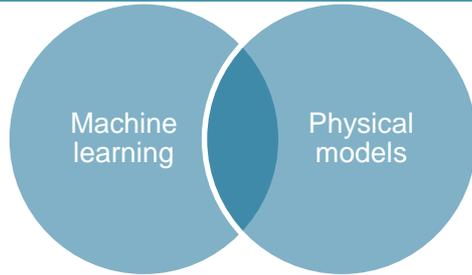
Estimates should be regarded as indicative only, as they are based on broad assumptions made from interview feed-back and anecdotal experience, aggregated to a NCS level.

The DNV GL estimates still confirm earlier estimates made for OG21 related to the high value creation potential of digitalization technologies (Rystad Energy, 2019). For instance, big data exploration analytics was in that study found to hold a potential of 1900 million boe, as compared to the DNV GL estimate (related to ML alone) of 950 million boe over a 30 years period.

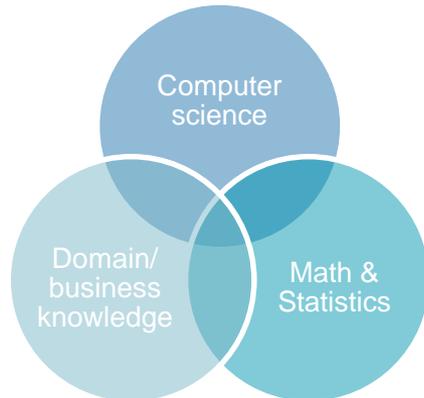
The DNV GL study also confirms the view expressed by OG21 earlier that the value of digitalization to a large extent materializes through the integration with other advanced technologies such as field model optimization, automated drilling control, predictive maintenance and unmanned platforms.

As a subset of digitalization, AI and ML would be part of the toolbox to realize value from such technologies.

ML is part of the toolbox – sometimes it will do the trick, other times alternative tools may be better



A combination of ML with physical models could in many cases improve results (DNV GL, 2020)



Applying ML is a cross-disciplinary effort

Machine learning identify patterns and trends from data, but do not “understand” physics. ML is preferred in cases where ML alone or in combination with conventional solutions provide better results than alternative solutions. It should however be recognized that ML capability and quality are rapidly being improved. ML solutions that currently might seem inferior could over time outperform traditional solutions. In such a situation it takes leadership and courage to deviate from a notion that new technologies already from 1st attempt must outperform incumbent technologies.

To improve the chances for ML success, the following should be considered (see e.g. DNV GL RP 0510 for further guidance):

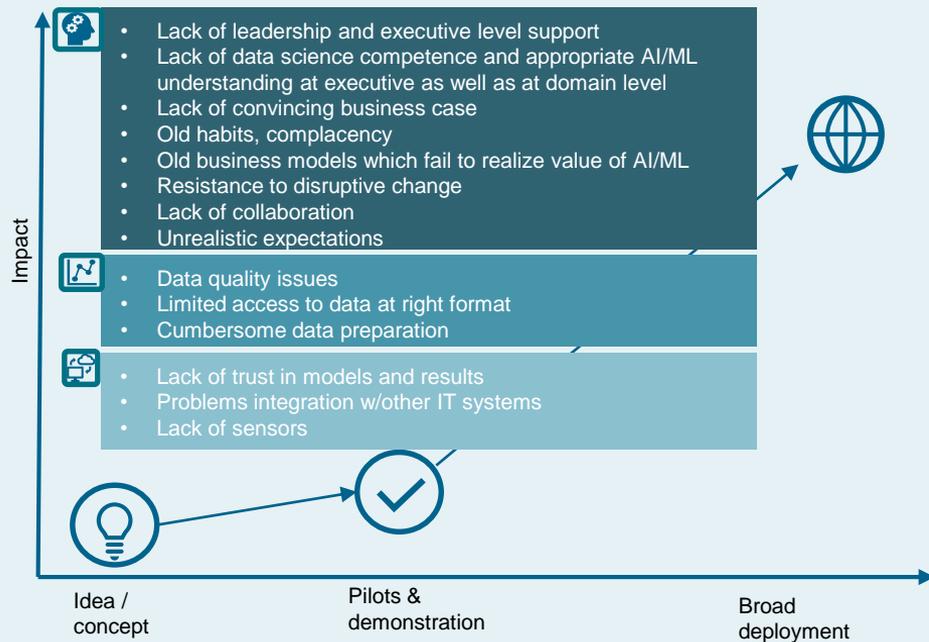
1. The problem is well understood and can be described accurately.
2. ML algorithms exist that are suitable for the problem.
3. ML solutions could provide better results than physical models alone.
4. Data can be made available with sufficient quality and in the right format at reasonable costs, both during the model training and the deployment phases.
5. Domain experts are closely involved in building and validating the ML model.

A combination of ML models with physical models (1st principle models) is recommended where physical models exist. This would especially be helpful in cases where events occur rarely and therefore provide limited datasets for ML model training (like failure of a component or system trips).

Before applying ML, risks and the criticality of decisions should be evaluated. Risk evaluations should in addition to safety and business risks, also include ethical implications as well as responsibility for decisions made based on results from ML models.

ML success requires more than new technology – organizational capability and data management equally important

Challenges and barriers to ML adoption, (DNV GL, 2020), (IDC, 2020)



Legend:



Technology

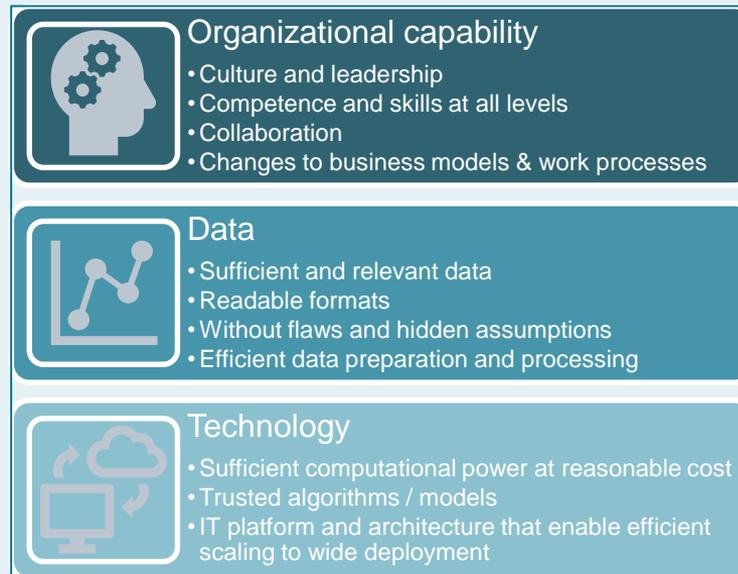


Data

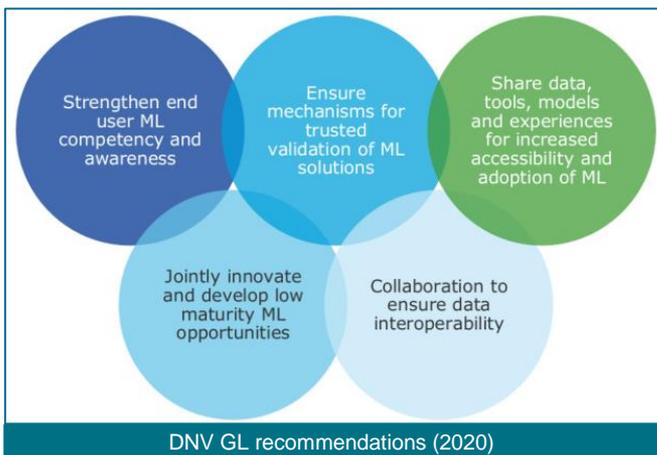


Organizational capability

ML success require maturity along 3 dimensions



OG21 supports recommendations put forward by DNV GL, and stresses the importance of technology leadership



DNV GL has through their bottom-up study approach on Machine Learning, identified 5 areas of particular importance for accelerating technology development and use.

OG21 has evaluated the 5 recommendations and support the view that they have a high potential for value creation in the Norwegian petroleum sector. We also find that all recommendations are actionable. 2 of the 5 recommendations identified align well with earlier OG21 recommendations identified through broader-scope analyses:

DNV GL recommendation (2020)	Related earlier OG21 recommendations
Ensure mechanisms for trusted validation of ML solutions	Oil companies should use common technology qualification procedures (OG21, 2018). The industry should continue its efforts on standardization to simplify implementation of new technologies (OG21, 2016)
Collaboration on data interoperability	Industry enterprises should collaborate on developing procedures and standards that enable data interoperability and efficient data sharing (OG21, 2018)

The DNV GL report has identified barriers and drivers related to leadership and culture, without specifically addressing such issues in the recommendations. OG21 has in previous studies emphasized the paramount importance of executive level ownership of technology for the successful implementation of technology (OG21, 2018).

OG21 strongly believes that executive level leadership is needed to recognize and support disruptive technologies such as ML. It takes courage to deviate from the notion that new technologies already from 1st attempt must outperform incumbent technologies. The earlier OG21-recommendation on this topic has therefore been repeated in this OG21 report.

Conclusions

- Machine Learning is transformative and requires technology leadership, full exploitation of the data and new processes and skills.
- The use of ML within the Norwegian oil and gas industry is in its infancy, characterized with many pilot initiatives. Few of these have been scaled and put into active use.
- Significant opportunities have been identified within all disciplines, in particular related to reduced GHG, reduced well delivery time, reduced OPEX, added volumes and accelerated production.
- The Norwegian oil & gas industry would have to step up its efforts significantly to fully seize this ML opportunity and release its potential. The industry capitalizes on a very small fraction of the value of the vast amount of data available for use.
- ML is part of the toolbox – choose the right tool for the task, but recognize in technology application strategies that AI/ML quality improves rapidly.

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OG21 Recommendations

#1 – Executive level technology leadership:

I

- Technology responsibility should start at the executive level and be distributed throughout the organization.
- Executive level technology managers should make sure that technology opportunities are identified and communicated to potential technology providers in a timely fashion.

#2 - Strengthen end user ML competency and awareness:

I

A

- Continued education for leaders, staff and domain experts in AI/ML, tailor-made to each group, covering basics, methods, applications and examples of use cases.
- Collaboration between universities and industry in defining, developing and delivering (short & long term) ML curriculum.

#3 - Collaboration on data interoperability:

IO

R

- Collaboration to ensure data interoperability (Technical, Semantic, contractual, legal) and standard application programming interfaces (APIs) for the oil and gas industry.
- Facilitate access to public and subscription-based data, data exchange and trading.

#4 - Ensure mechanisms for trusted validation and quality assurance of ML solutions:

IO

R

- Standardize practices for validation of ML based solutions (e.g. DNVGL- RP-0510 Framework for assurance of data-driven algorithms and models).
- Validation requirements should reflect criticality of decisions.
- Enforce transparency via regulatory requirements for validation of ML models if applied in business or safety critical decision processes.

#5 – Collaboration on ML solutions and data management in selected areas:

IO

I

- Cross industry collaboration for developing ML solutions in selected areas with common interest, e.g. Environmental monitoring, Energy efficiency, Maintenance optimization.
- Share data within selected areas of common interest where value of sharing outweighs loss of competitive edge.
- Clarify risks and liability related to the use of shared data.
- Collaboration btw. individual industry enterprises within areas where risks or competition considerations prevent broader industry initiatives.

#6 - Share lessons learned:

IO

R

I

A

- Sharing lessons learned for accelerated learning and ML adoption, e.g. information on experiences with ML algorithms, case studies and data processing.

Suggested action ownership:

I

Industry

IO

Industry organizations

A

Universities / research institutes

R

Regulators

LITERATURE AND REPORTS

- DNV GL – *OG21-study on Machine Learning in the Norwegian petroleum industry*, (2020)
- Konkraft, *The energy industry of tomorrow on the Norwegian Continental Shelf*, (2020)
- NPD, *Resource report*, (2020)
- OG21, *Technologies for cost and energy efficiency*, (2019)
- OG21, *Risk assessments and impact on technology decisions*, (2018)
- Rystad Energy, *Technologies to improve NCS competitiveness*, (2019)
- Economist, *Technology quarterly*, June 11 (2020)
- IDC, *Artificial Intelligence - From experiment to enterprise strategy*, (2020)

OG21 PROJECT TEAM

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