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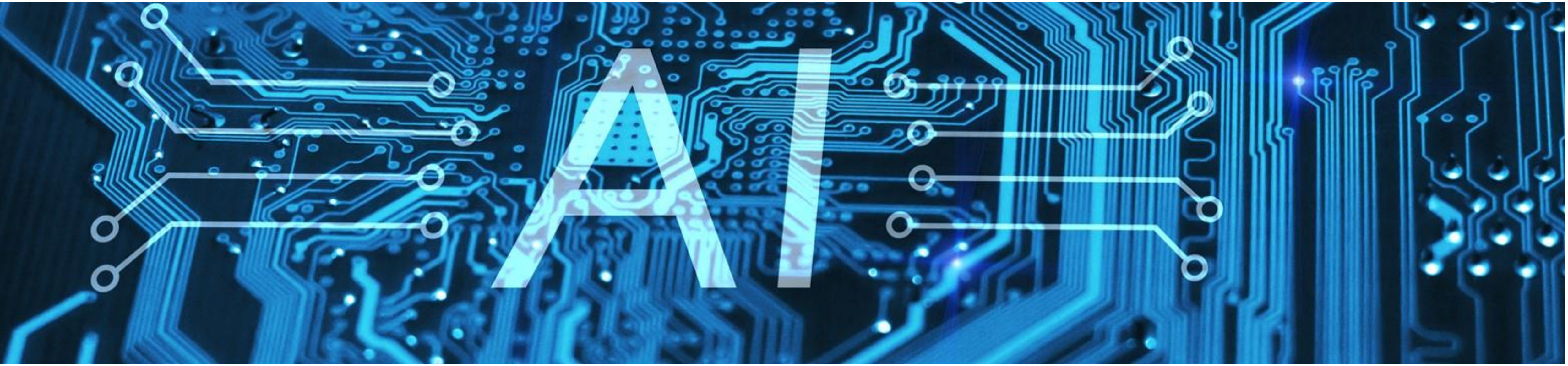


OIL & GAS

# OG21 – Study on Machine Learning in the Norwegian petroleum industry

## Final Report: Conclusions, recommendations and findings

# OG21 – Study on Machine Learning in the Norwegian petroleum industry

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| Prepared by/Contact Person:<br>Hans Petter Ellingsen (PM), Sture Angelsen, Ole Kristian Sollie, Abdillah Suyuthi, Rajesh Mistry, Per Myrseth, Ole Gunnar Tveiten (AGR) | Position:<br><br>OG21-team | Signature:<br>Hans Petter Ellingsen<br>Digitally signed by Hans Petter Ellingsen<br>Date: 2020.09.24 11:46:16 +02'00' |
| Verified by:<br>Frank Børre Pedersen | Position:<br>Programme Director | Signature: Pedersen, Frank Børre<br>Digitally signed by Pedersen, Frank Børre<br>Date: 2020.09.24 12:09:40 +02'00' |
| Approved by:<br>Geir Egil Eie | Position:<br>Head of Department | Signature: Angelsen, Sture<br>Digitally signed by Angelsen, Sture<br>Date: 2020.09.24 16:41:08 +02'00' |

# Executive summary

### Background

Machine learning (ML) is widely applied in various industries and in the society. ML is increasingly becoming an important element also in the petroleum industry. OG21 have defined the following objectives for this work:

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

These issues have been addressed via OG21-workgroups, interviews with operators, academia in Norway and abroad, and literature search.

### Conclusions

- The use of ML within 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 TTAs in particular related to reduced GHG, reduced well delivery time, reduced OPEX and accelerated production.
- The Norwegian oil & gas industry should 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 transformative and requires digital leadership, full exploitation of the data and new process and skills. ML pilots will not bring sustainable change and value unless scaled and broadly adopted.

### Recommendations to accelerate ML

- ✓ Strengthen end user ML competency and awareness.
- ✓ Ensure mechanisms for trusted validation of ML solutions applying best practices and standards for ML validation (e.g. DNVGL-RP-0510 Framework for assurance of data-driven algorithms and models)
- ✓ Jointly innovate and develop low maturity ML opportunities.
- ✓ Collaboration to ensure data interoperability
- ✓ Share data, tools, models and experiences for increased accessibility and adoption of ML

# OG21 – Study on Machine Learning in the Norwegian petroleum industry

Machine learning (ML) is widely applied in various industries and in the society. ML is increasingly becoming an important element also in the petroleum industry. OG21 have defined the following objectives for this work:

**1**

How big is the opportunity related to ML on the Norwegian Continental Shelf (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?

These issues have been addressed via OG21-workgroups, interviews with operators, academia in Norway and abroad, and literature search.

# What is Machine Learning (ML)?

> Machine learning is defined as ***giving computers the ability to learn*** *from* ***data*** *without being given explicit rules by a programmer*
>
> *(Arthur Samuel, 1959)**

INPUT
**X**

PREDICTOR
F**(X)**

PREDICTION
**Y**

**Machine Learning or Data Science Methodology**

The predictor = ML model is obtained through *model training*.

We let the computer to learn the rules/patterns automatically from useful features of existing data.

The main benefit of using ML is that no prior assumption on the (physical) process is required. This could enable us to solve problems where first principle model is not available.

Another main benefit is that the inference time is relatively short as compared to e.g. physical-based simulation. This could enable us to get results more efficient.

*Samuel, A.L., 1959. *Some Studies in Machine Learning Using the Game of Checkers*. IBM Journal of Research and Development, Vol.3, Issue:3, Pg.210-229.

# Steps used by the project to identify, define and evaluate ML opportunities

**DESCRIBE** types of ML

- Types of ML, possibilities and limitations
- State of art, maturity
- Literature studies, interviews and contact with relevant O&G parties

**DEFINE** opportunity list and link to ML solution. Assess initial values

- Problem description
- Current state in the industry
- ML examples
- Initial value estimation towards project objectives
- Prioritization of ML opportunities for detailed evaluation
- Literature study and mapping of status

**EVALUATE** if ML solution is fit for use within acceptable risk and cost. Provide recommendations

- Detailed evaluation of technology readiness, risks, enablers and barriers for adoption and use.
- Provide recommendations to stimulate development and adoption of value-adding ML
- Access to data with sufficient quality and security
- Detailed value assessment towards project objectives
- Recommendations

# Outline

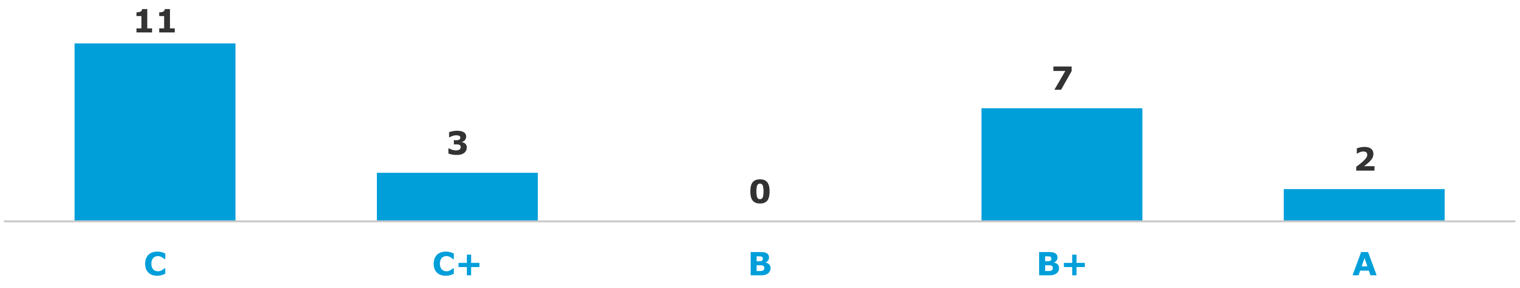
# 1 Summary, conclusion and recommendations

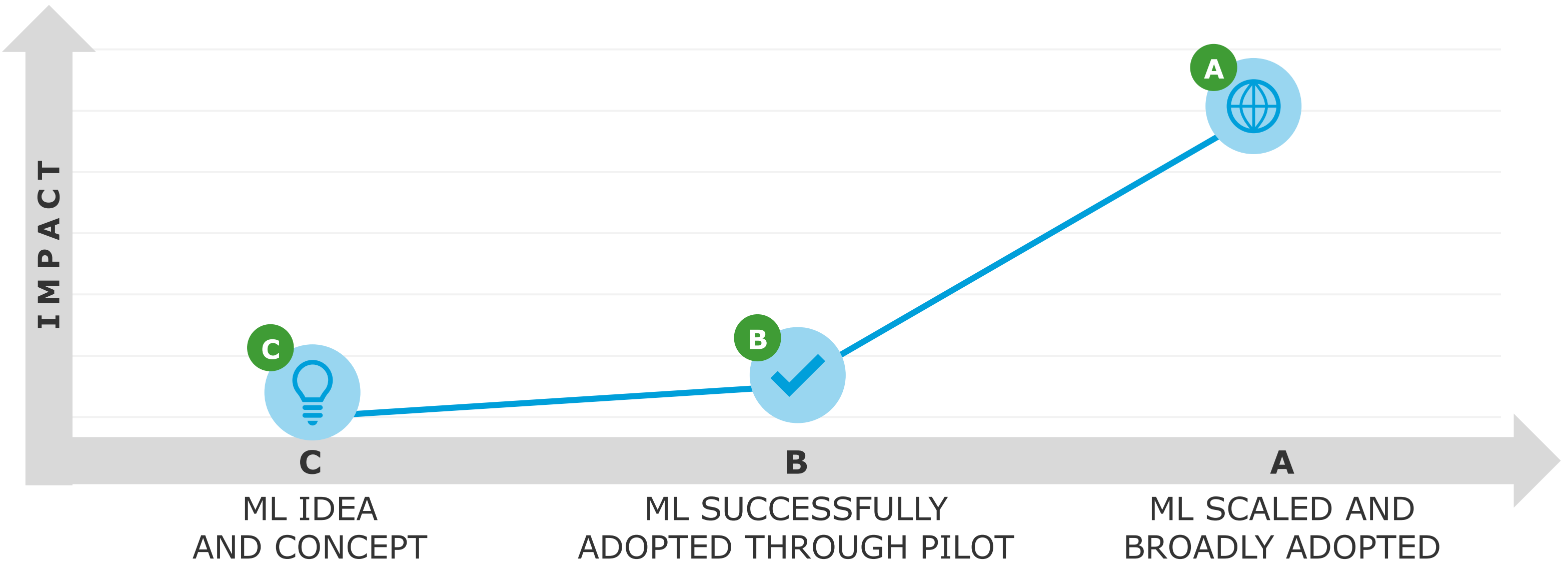
# Summary and conclusions

## The first step has been done, but the next step is of a different magnitude

- The use of ML within 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 TTAs in particular related to reduced GHG, reduced lead time to first oil, reduced well delivery time, reduced OPEX and accelerated production.
- The Norwegian oil & gas industry should 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 transformative and requires digital leadership, full exploitation of the data and new process and skills. ML pilots will not bring sustainable change and value unless scaled and broadly adopted.
- ML should be *combined* with other digital solutions, analytics and good industry practice  to release the potential.
- The relevance of ML is cases where ML alone or in combination with conventional solutions is significantly better then alternative solutions.

**Number of ML solutions with different levels of progress**



# Summary of findings; Opportunities and overall effect per main area (1 out of 2)

| Application areas (TTA): | | Key opportunities | (ML) Potential | Probability of success(PoS) (reflecting barriers and ML maturity) | Estimated Potential for NCS |
|---|---|---|---|---|---|
| 1 | Energy efficiency and environment | Main contribution from ML applied in production optimization & energy efficiency. | 10% GHG reduction | ~70% | Reduction in GHG of about 0.9 Mega ton representing ca. 6% (ref total GHG; 14.2 Mega ton/year) |
| | | ML could improve environmental monitoring/oil spill response and subsea leak detection | Reduction in environmental risk/ impact and/or oil spill volumes | ~70% | ML could contribute in reducing the environmental risk on the NCS. Quantification is difficult. |
| 2 | Exploration and increased recovery | Better reservoir management (IOR).<br><br>ML is unbiased, thus offer an opportunity for more objective reservoir modeling.<br><br>50% faster model update. | Reduced time and manning in operations phase due to more efficient seismic interpretation and modelling.<br><br>ML applied for reservoir management and optimization leading to less energy consumption and GHG emmisions due to reduced water production and gas injection.<br><br>2-20% increased recovery in simulation models, mainly as a consequence of optimized infill targets. | ~50% | Reduced time and manning in operations phase due to more efficient seismic interpretation and modelling corresponding to yearly saving of 100 MNOK in OPEX.<br><br>Notes:<br>• Increased recovery potential high but not quantified due to high uncertainty in how the ML cases and potential will apply to different reservoir models.<br>• Reduced GHG not quantified due to uncertainty in GHG impact from reduced water production and gas injection. |
| 2 | Exploration and increased recovery | Better understanding of prospects and better basis for decision to drill.<br><br>Faster seismic processing results (50%).<br><br>Automatic fault and horizon interpretation. | Better drilling decisions using ML in exploration leading to one additional discovery per year.<br><br>About 4 months accelerated production due too faster seismic processing and interpretation. | ~90% | Assumed one additional discovery of 5 mill Sm3 o.e. per year<br><br>Reduced time and manning in exploration phase estimated to 60 MNOK.<br><br>Note:<br>The value of the accelerated production is small since the entire project (including the cost) is accelerated. Please see page 75 for details. |



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# Summary of findings; Opportunities and overall effect per main area (2 out of 2)

| Application areas (TTA): | | Key opportunities | (ML) Potential | Probability of success(PoS) (reflecting barriers and ML maturity) | Estimated Potential for NCS |
|---|---|---|---|---|---|
| **3** | Drilling, completions and intervention | Autonomous drilling and parameter optimisation to increase efficiency.<br>Reduced NPT (Non-prod. Time) via ML incident detection algorithms. | 20% reduction of well delivery time<br>20% reduction in sidetrack | ~80% | ▪ Drilling cost reduction; 3-4 bNOK/year<br>▪ GHG reduction of 0.06 Mega ton, representing 6% of drilling activities release (1.06 Mega ton) |
| **4** | Production, processing and transport | CBM, Predictive maintenance & operator advisory models, (process digital twins) can significantly improve performance.<br>However, good alternative to ML exists and should be applied in parallel to ML. | 15% OPEX reduction<br><br>6-7% accelerated production | ~60% | ▪ OPEX reduction potential; ~ 2 bNOK/year<br>▪ Accelerated production potential via CBM & production optimisation corresponds to ~ 8 mill Sm3 o.e. per year |

# Multiple barriers identified to successful ML adoption

- ML applications often requires unique sets of competence and skills within data science and domain knowledge with very limited availability
- Difficult to break out of "business as usual" way of working. ML applications mostly require
  - Collaboration amongst multiple stakeholders
  - Data washing and preparation
  - Communication and data transfer between multiple IT systems
  - New work processes
  - Highly skilled resources combining domain knowledge, data science and programming
- Changes and efforts required for ML adoption requires a sound business case which is not easy to develop
- Organizational factors related to
  - Resistance to change
  - Lack of trust in ML models
  - Insufficient leadership
- Data availability and quality is a challenge, in particular for older installations.  Diligent management of data quality is needed for ML to succeed

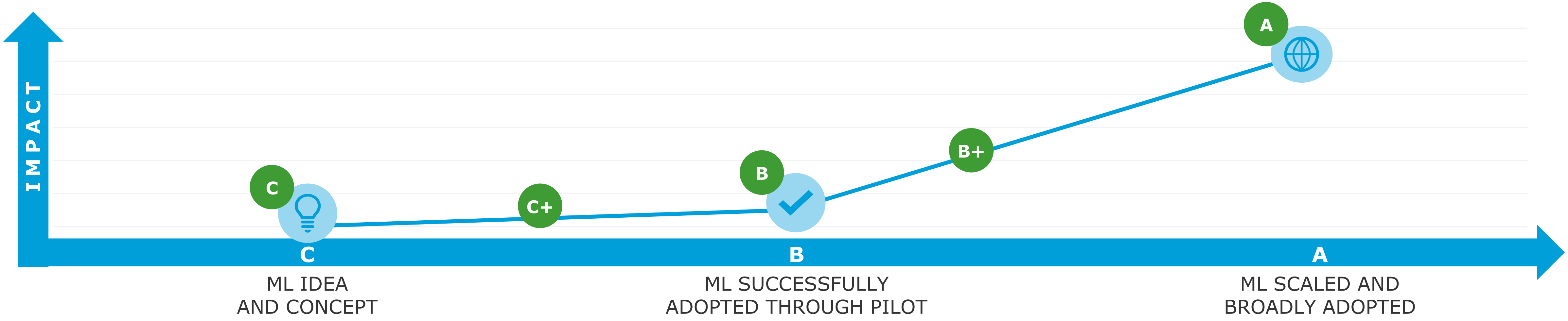
# Different ML barriers at different stages

**C barriers – Knowledge, business case and complacency**

- Lack of ML literacy and business case. Clever engineers may see the potential, but leaders are not familiar with ML and would need a clear business case to act on good ideas.
- Old habits and complacency prevents the industry from acting on the ML opportunities.

**B barriers – Organizational**

- Despite that pilots show a potential, broad implementation requires that the data preparation process is streamlined and automated, new software solutions are developed and staff is trained in new tools and new ways of working. Strong business case for ML often comes with a big sum of required disruptive changes.

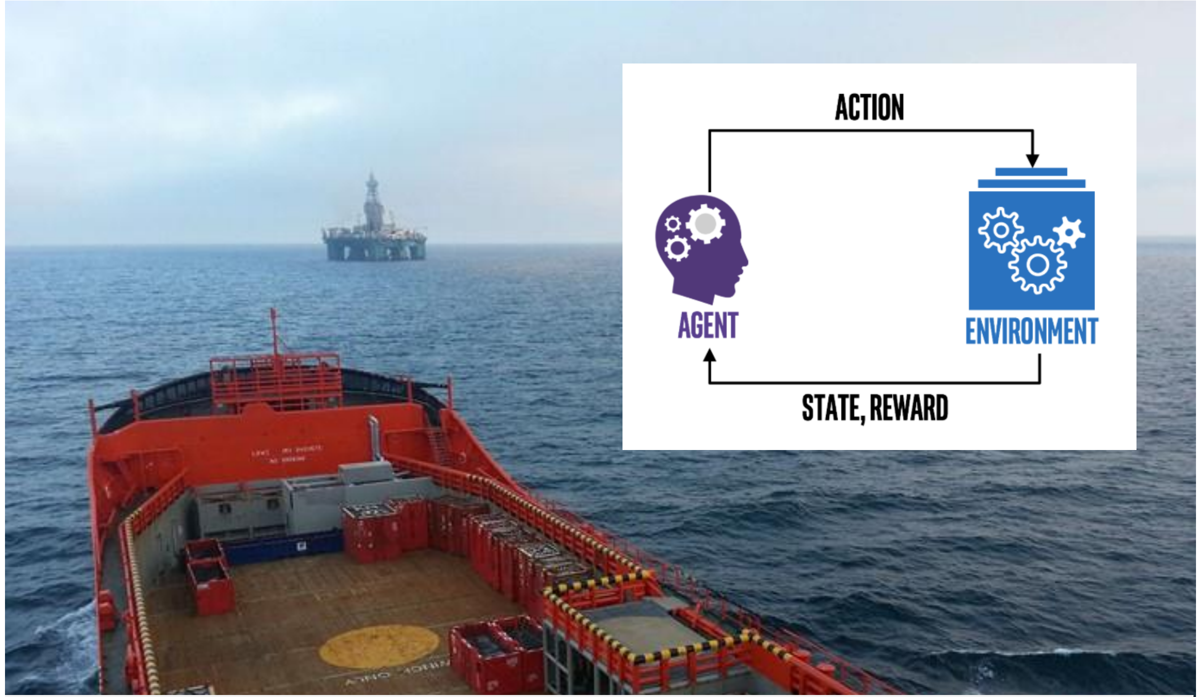



**"The barrier is to get ML solutions fast enough in the hands of the end users of ML"**

(Quote from operator representative about main barrier for ML being scaled and applied within the organization)

# Key findings from study with regards ML and capability of the Norwegian Petroleum Industry to apply ML

- ML/AI is increasingly becoming more available and accessible in commercial applications, platforms, software and apps making it more ready to be adopted.
- There have been several hype and disappointment cycles for ML over decades. The ML technology is now more widely deployed and conditions for ML success are now much better compared to previous hype and cycles.
- ML niche players have emerged and helped support proof of concepts for the Norwegian Petroleum industry to capture an initial ML potential and value.
- Despite a steep learning curve for ML for approximately the last 5 years, there is still a lack of ML literacy throughout the industry and as a result many concepts, ideas and opportunities for adoption of ML are left unexplored.
- Some examples of ML collaboration in the industry are identified, but more commonly knowledge transfers and re-adoptions from successful ML pilots are very limited.



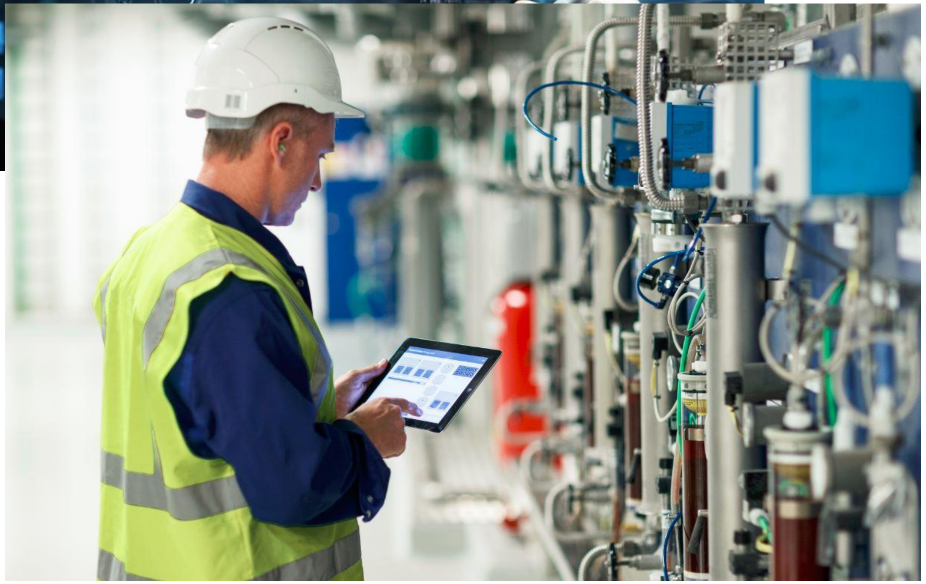

**"The machine learning revolution has been built on three things: Improved algorithms, more powerful computers on which to run them, and -thanks to the gradual digitization of society – more data from which they can learn. "**

(Quote from Economist June 13th - 19th 2020)

# A strong advice from pilots/test cases

- The relevance of ML is cases where ML alone or in combination with conventional solutions is significantly better then alternative solutions, i.e. conventional solutions/models will be used if these provide good results.
- ML models combined with 1st principle is recommended where such models exists.  In particular for cases where few events occur that can be used as basis for an ML model (like failure of a component, system trips).
- Develop a sound business case.
- Requirement for strong leadership to drive change and patience in implementation.
- Close collaborations of multiple stakeholders, in particular between data scientists and domain experts.

**"Computer science experts should work closely with discipline experts – to understand their challenges, learn from each other, and identify ML opportunities together to streamline processes and operations."**
(Quote from drilling technology expert about the importance of close collaboration between data scientists and domain experts for successful application of ML)

# Areas currently holding back ML and recommendations for acceleration

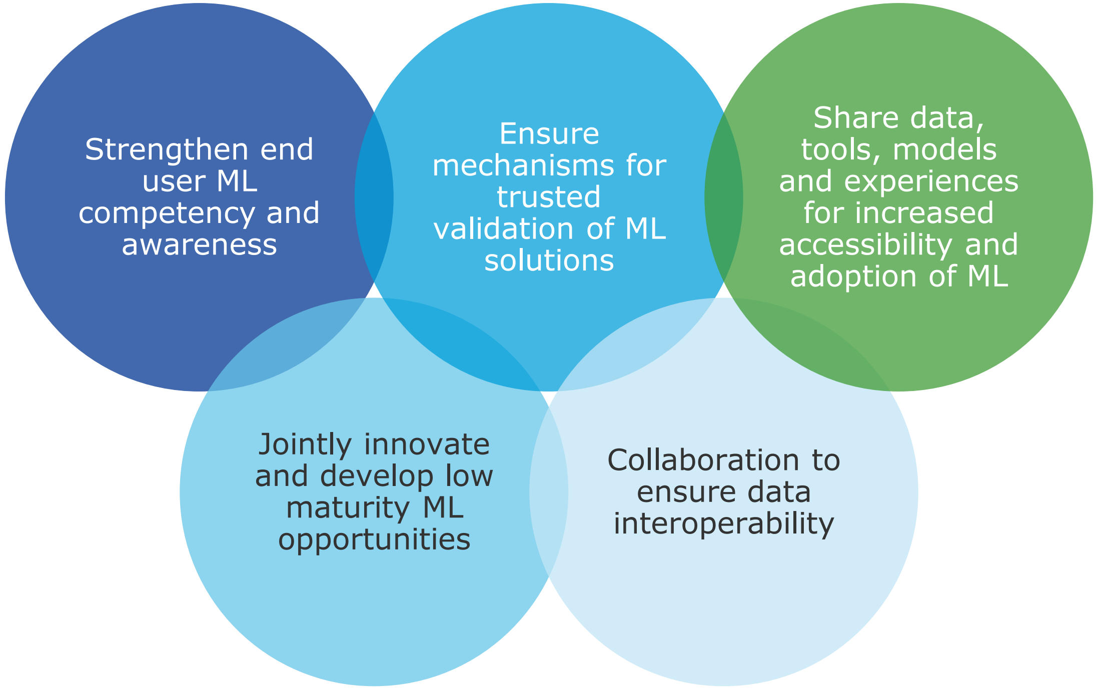
## Areas currently holding back ML

1. Lack of ML competencies, skills and awareness of its potential. Several maturity "level C" ML opportunities have not been explored and tested. Good ideas are left at the drawing board.
2. Knowledge transfers and re-adoptions from successful ML pilots and collaboration within the ML domain are very limited.
3. Lack of transparency and trust in ML solutions; e.g.
   a) domain experts do not trust results
   b) license partners due to lack of insight and proof of algorithms
4. For some ML opportunities data silos and insufficient amount of data prevents industry from exploiting the full ML potential and value through collaboration and sharing. Lack of interoperability between data systems and legal frameworks for sharing are perceived challenges, which with commitment and resilience can be effectively managed.

**"The oil & gas industry must realize that it has become an IT industry. Managers are primarily engineers in the oil & gas industry and have a strong foot on the hardware. ML is transformative and it goes fast. We need to educate the industry. Otherwise it will be out of business."**

(Quote from technology developer and researcher about the challenge related to most managers being engineers and not seizing the ML opportunity)

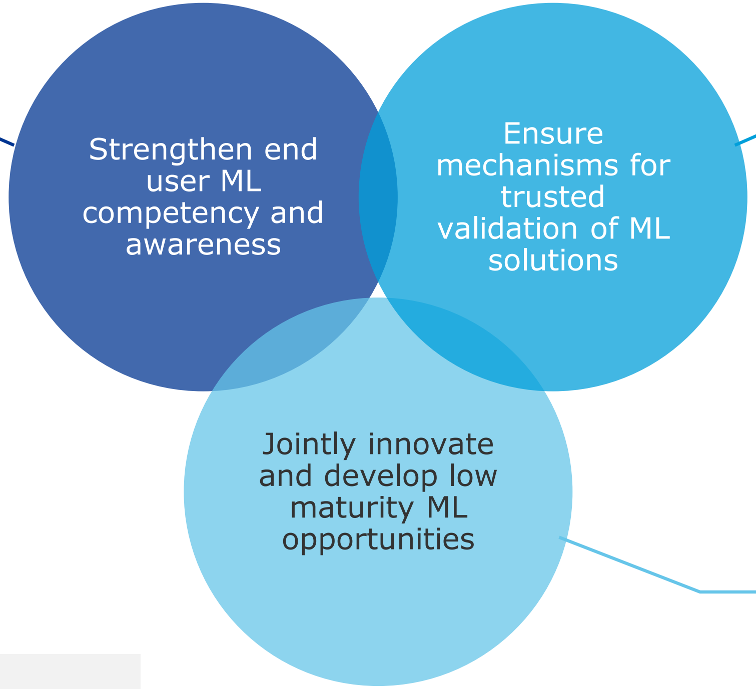
## Recommendations for acceleration



# Recommendations – Competency, ML trust and innovation

## Build data science and ML competence, build trust in ML and innovate

- Continued education (short term) for staff, leaders and discipline experts in AI/ML basics, methods and applications.
- Collaboration between universities and industry in defining, developing and delivering (short & long term) ML curriculum.




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

- Initiate Joint Industry initiatives within targeted areas – in order to share development cost, test applicability and concepts amongst operators, service providers and academia. Examples of low maturity high potential areas include:
  - Logistics
  - Drilling fluid management
  - Process digital twin
  - Inspection and integrity management

> **"Sharing a decision basis based on ML in a license is easy, but to validate the decision basis is a challenge"**
>
> (Licensee about the challenge to validate ML results)

# Recommendations – Industry sharing and data interoperability

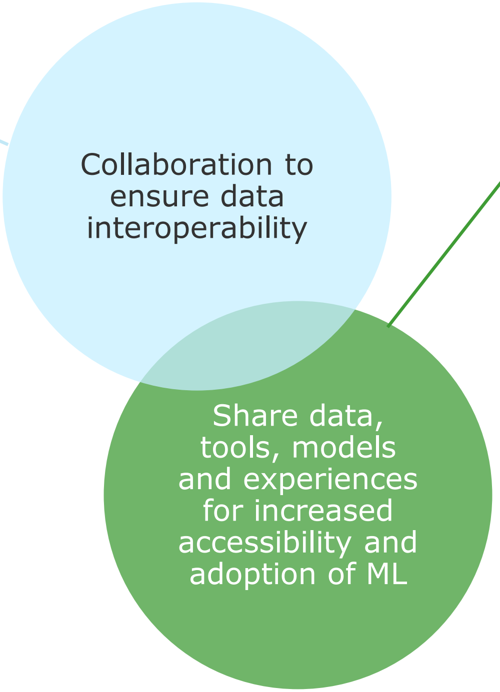
## Enable data exchange and trade as well as cross company and industry learning

**Data interoperability**

Collaboration to ensure data interoperability (Technical, Semantic, contractual, legal) and API's for the oil and gas industry.

Facilitate access to public and subscription-based data, data exchange and trading.

The READI (REquirementAsset Digital lifecycle Information)* project is in the process of developing interoperability standards and solutions and could hence be part of the solution to facilitate sharing of data.




**Data sharing**

Collaborate in targeted areas in which data silos and insufficient amount of data prevents industry from exploiting the full ML potential and value through collaboration and sharing, e.g.

a) Cloud & ML based reliability database providing guidance for maintenance optimization. (sensitive to design, maintenance tasks, load history, etc..).
b) Set-up DISKOS for ML use with the aim to discover new resources in existing data.

**Tools**

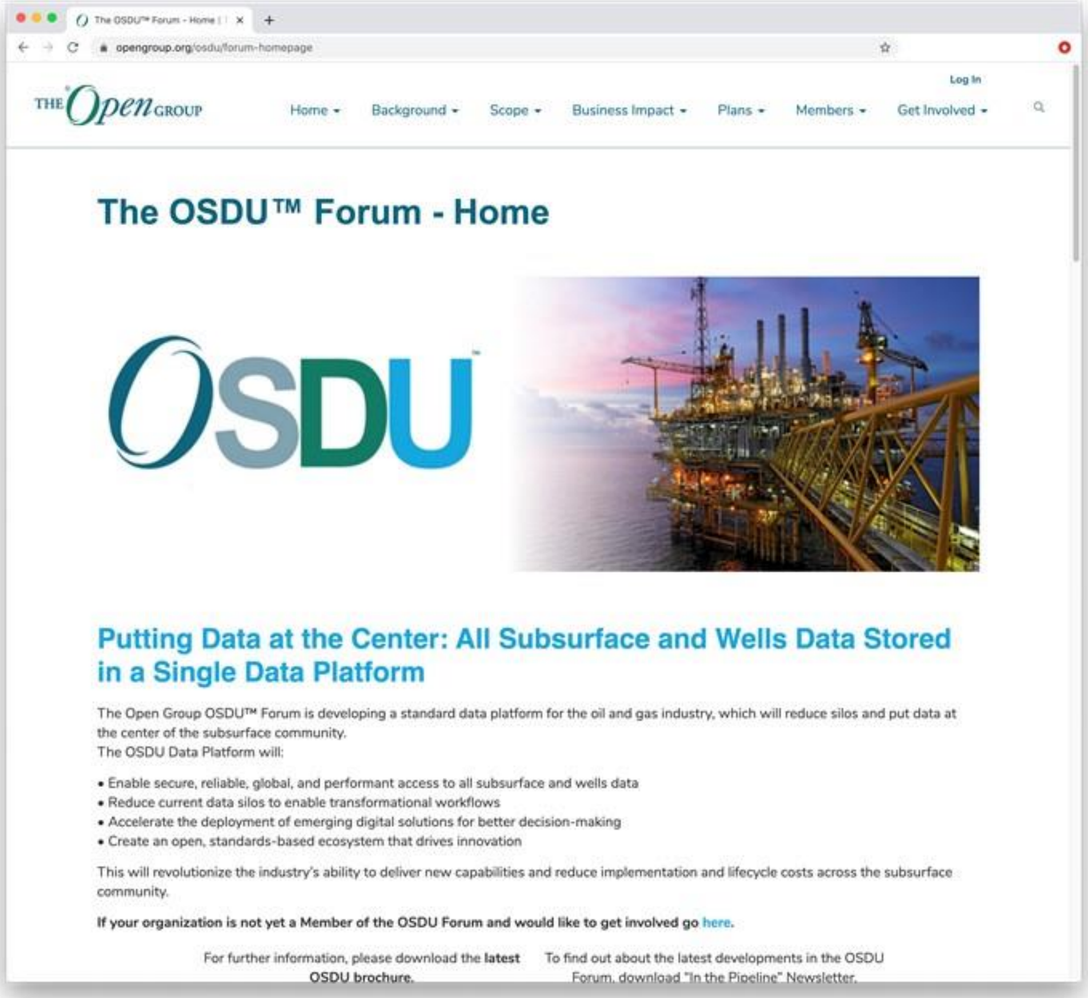
Sharing lessons learned, successful ML algorithms, case studies, etc. for accelerated learning and ML adoption

Cross industry collaboration for developing ML solutions in targeted areas with common interest, e.g.

a) Environmental monitoring
b) Energy efficiency
c) Maintenance optimization / integrity management

* READI JIP Ministry of Petroleum and Energy, 24. April 2019, SectorBoard Petroleum

# OSDU shows how the industry should work together to release the ML potential




**Key enablers**

- ML applications and algorithms are becoming increasingly available and accessible for all.

**The OSDU platform will*

- Enable secure, reliable, global, and performant access to all subsurface and wells data.
- Reduce current data silos to enable transformational workflows.
- Accelerate the deployment of emerging digital solutions for better decision-making.
- Create an open, standards-based ecosystem that drives innovation.

* From OSDU website; www.opengroup.org/osdu/forum-homepage

**"The market currently consumes applications based on desktop. Many initiatives exist to tear down the silos, of which OSDU is the most important."**

(Quote from ML technology provider about the importance of making ML available and accessible)



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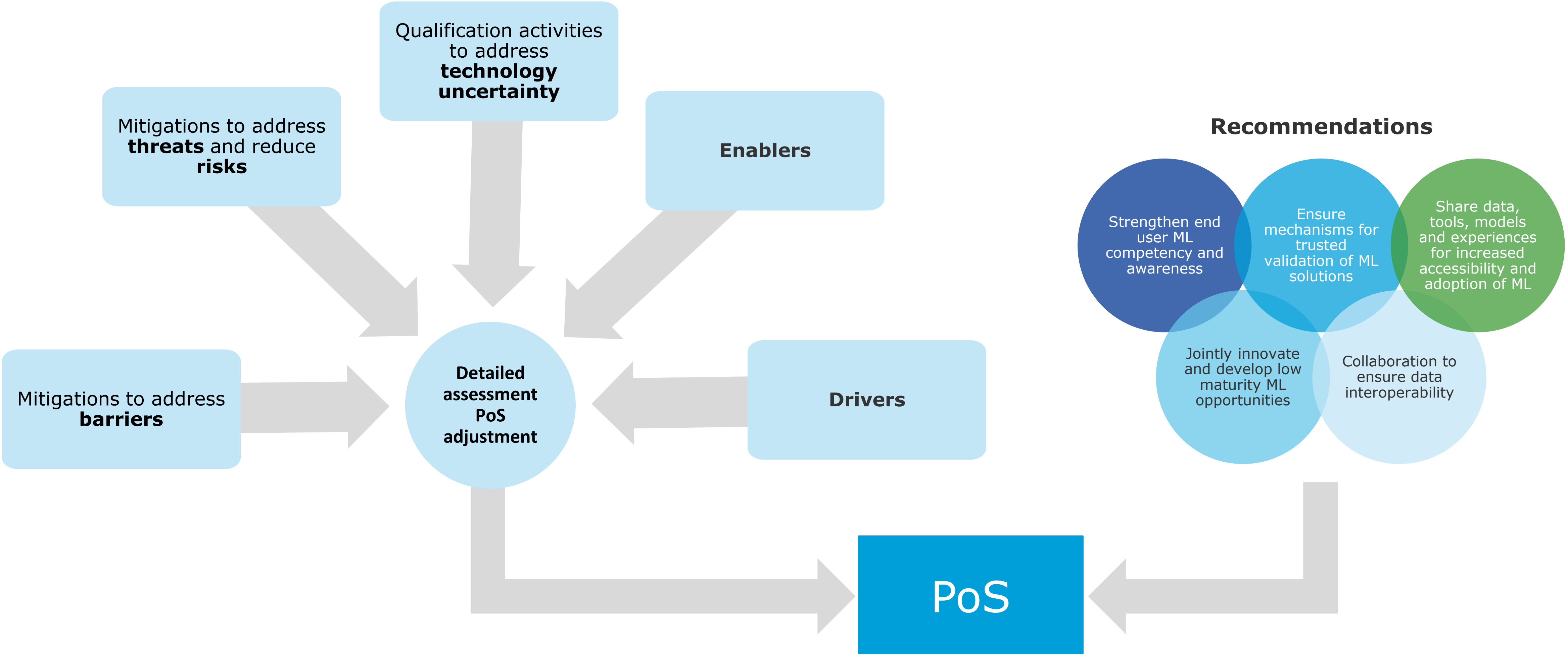
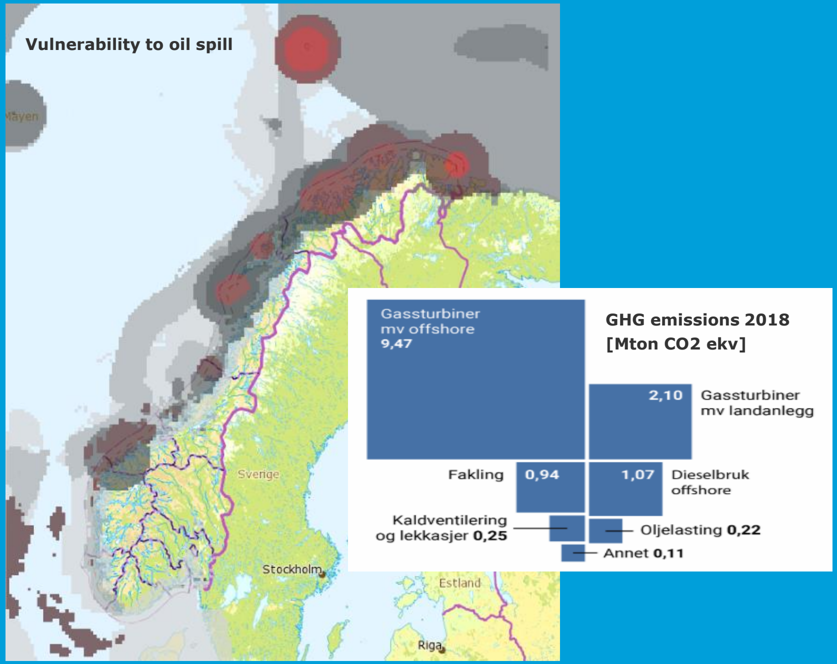
# Probability of Success (PoS) depends on numerous factors but will be increased and supported by the recommendations if implemented



# TTA1 Summary

# Energy efficiency and environment



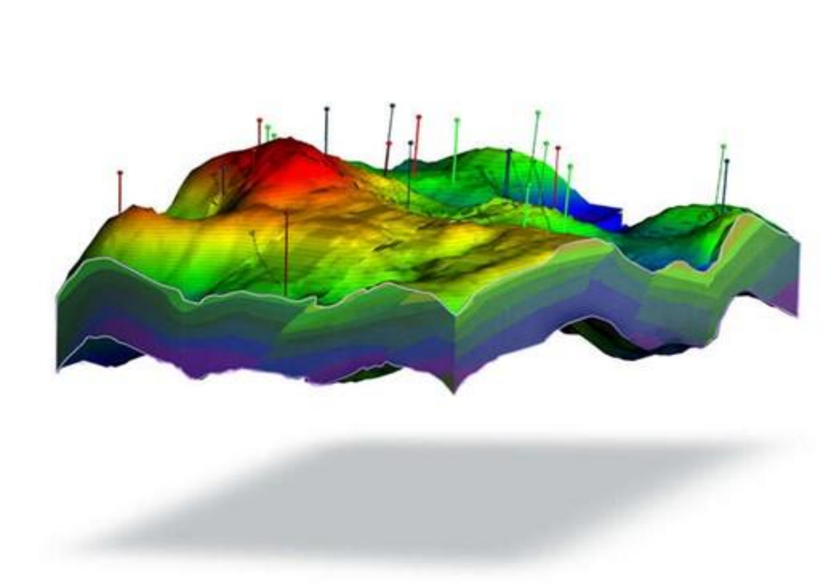

| ML Opportunities | |
|---|---|
| 1.1 | Environmental Monitoring |
| 1.2 | Subsea leak detection |
| 1.3 | Electrification of offshore installations |

**Main conclusions – TTA1:**

- ML is an important part in order to establish a better understanding of natural ecological variations and thereby enable much earlier detection of possible environmental impact.
- Real time monitoring, or close to real time, is looked upon as the next natural steps in environmental monitoring. One need to prove early detection of environmental impact and ability to react fast, especially in sensitive areas. Real time monitoring could facilitate decisions related to disposal of drill cuttings and/or produced water in sensitive areas. It could also play a part in oil spill operations where monitoring of oil slick combined with weather data and ecological data could be important for detecting the right oil spill measures. ML is essential in order to develop real time monitoring.
- When it comes to remote sensing ML could play a role in characterization of oil spills, however more work is needed in order to develop and improve the technology. Access to site data from oil spill is a barrier.
- There is a potential for application of ML to detect leakages. The most promising application lies in adding ML to already existing systems as mass balance. This will enable detection of small leakages, which also is the type of leakages that occurs most often on the NCS. ML would also have an advantage as it can adapt to changing production profiles, which is a current challenge when it comes to mass balance systems today. Subsea sensoring is costly, hence improving current system with ML could be more cost-effective. Having said that, development of subsea sensoring for leak detection is ongoing and could provide cost effective and robust solutions in the future.
- ML will not be the single key driver for bringing the costs down for integration of wind power offshore, however ML could possibly contribute with necessary cost reduction by reducing conservatism in design, optimize over the lifetime of the windfarm.
- ML is already a part of the solution for power prediction to ensure optimal energy production for the facilities (combined with back-up solutions).
- ML could play a role in establishing power-hubs offshore. ML can contribute to optimize power supply-demand balance between the different installations attached to the hub, hence ensure an efficient operation of back-up solutions if needed.

# TTA2 Summary

# Exploration and increased recovery



| ML Opportunities | |
|---|---|
| 2.1 | Seismic Processing |
| 2.2 | Seismic Interpretation |
| 2.3 | Well log interpretation |
| 2.4 | Increased Oil Recovery (IOR) |

**Main conclusions – TTA2:**

- Generally, the oil and gas industry has taken on ML during the last 5 years. Exploration and increased recovery is the area where the industry has made the biggest progress in applying ML. Currently ML advances is expected to have impact on reduced lead time in seismic processing and interpretation, this may lead to less time from seismic processing and interpretation to decision to drill. The use of ML in the field production phase has enabled Fast Model Update (FMU) and Increased Oil Recovery (IOR).
- Use of huge 3D and 4D seismic datasets has recently opened a new era of seismic imaging enhanced by ML applications. Seismic companies have basically no barriers for adopting ML on seismic. Oil price fluctuations are posing a risk on continuous ML development.
- In terms of ML on field development analysis, Stanford University concluded through interview; ML has a good potential onshore with many similar fields. Field development in the North Sea, however, is hampered by a more complex infrastructure and requiring many agreements to be executed making it more difficult to copy the ML success from onshore field development.
- ML on seismic processing has been developed and put in production. Significantly faster processing, less human input have enabled less lead time for final product and better seismic. Better seismic results in:
  - a) Better geological models and less dry holes.
  - b) Better placed infill drilling
  - c) Less man-hours
- ML on Seismic Interpretation has resulted in automatic fault and horizon interpretation. This in turn means G&G interpreter can spend more time on creative work, generating better geological models, saving man-hours.
  - a) Better geological models and less dry holes.
  - b) Better placed infill drilling
  - c) Less man-hours
- Well Log Interpretation: Huge amounts of well logs can be re-interpreted in very short time with little man-power. In field development, this will support fast model update. In exploration this may identify missed pay and opening new prospective trends/targets, giving huge potential upside, oil and gas discoveries.
- Increased Oil Recovery: ML on reservoir modeling enables revision of geological and geophysical models using much less manpower. Fast Model Update provides better basis for infill targets, less dry wells (watered out) and better reservoir management.
- ML Challenges
  - a) Deep learning cannot understand the physics of complex non-linear processes.
  - b) ML works well when interpolating inside known data, limited predictability when extrapolating outside “the box”
  - c) All actions are based on existing data, resulting in a tendency of limiting thinking. E.g. the major improvements in field recovery and development have been achieved using totally new methods.
  - d) “Big data versus big mess” (Feedback in interview). This is not only a barrier, but is seen as a weakness, resulting in wrong conclusions or lack of trust.

**TTA3 Summary**

# Drilling, completion and intervention


| ML Opportunities | |
|---|---|
| 3.1 | Autonomous drilling and parameter optimisation |
| 3.2 | Detection of downhole incidents |
| 3.3 | Digital well planning |
| 3.4 | Drill fluid management |

**Main conclusions – TTA3:**

- The largest potential is within detection of downhole incidents for detecting drilling incidents (anomalies) like downhole vibrations, twist off, stuck pipe, losses, kick detection, Torque & Drag etc..
- Autonomous drilling is at an early stage with some use of ML embedded within the drilling controls. Control of drilling parameters can be done fully automatic today, but level of implementation is limited. Robotics for drill floor operations also being developed but is generally more complex and the contribution from ML is more limited.
- Some pilots conducted for digital well planning. This is an area requiring significant effort and time today and ML has a large potential to streamline and shorten the time and effort in the digital well planning process.
- ML is an important part of current commercial software and solutions for detection of downhole incidents, autonomous drilling and to some extent digital well planning today, but its full potential is not yet currently exploited. The main barrier for scaling and broad implementation has been identified to be lack of trust in following any advice provided by the ML models.
- Applying ML for Drilling fluid management and mixing was identified as a high potential ML opportunity not yet explored by the industry.
- ML can be applied with data logging through conventional drill pipe. A wired drill pipe would however enable a higher density of data from down hole tools and thereby improving the quality and output from ML applications.



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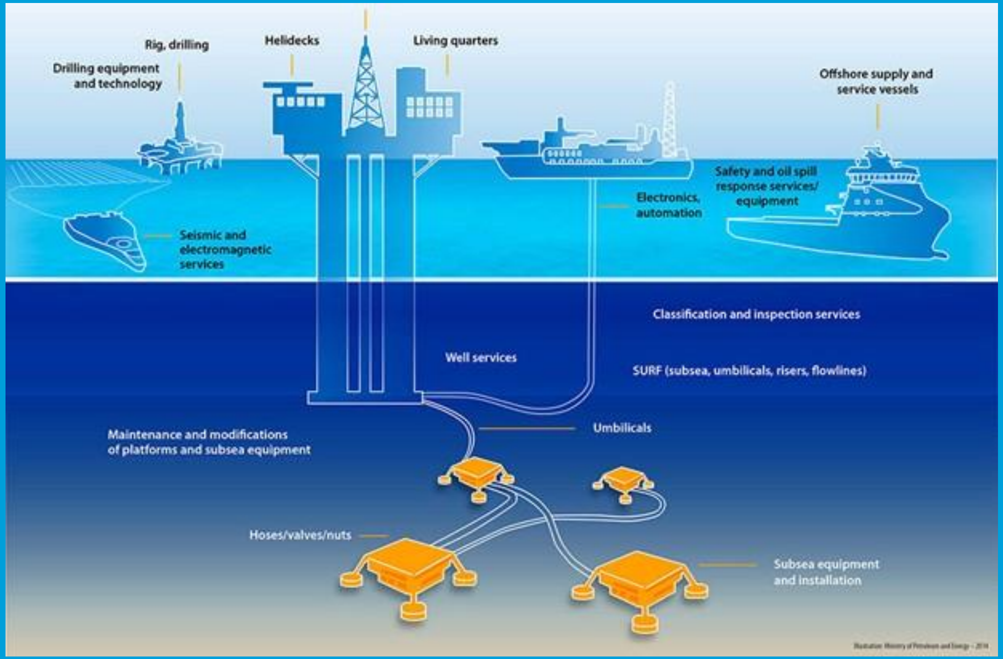
# Production, processing and transport




| ML Opportunities | |
|---|---|
| 4.1 | Predictive Maintenance & CBM |
| 4.2 | Production optimisation |
| 4.3 | Logistics optimisation |

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**Main conclusions – TTA4:**

- The largest potential is within **process control** to secure stable production by applying adaptive models and/or process based digital twins (process simulators) enabling:
  - Stable production
  - Control room decision support
  - Forecast models for enhanced operations
- These solutions exists today as commercial products (adaptive process control) or operator made solutions.
- Larger models (simulators) combined with ML will enhance these solutions, but represent a larger investments.
- Maintenance and inspection optimization via **CBM** (Condition Based Maintenance) is the second largest potential.  CBM will improve planning, optimal maintenance interval setting, prevent breakdown of equipment.  The effect is reduced cost and increased uptime.

# The most promising ML applications for TTA 1 and 2

| TTA | ML application | ML Potential* | | | | | PoS full scale (A) | ML maturity Index | Main barrier for implementation of solution |
|---|---|---|---|---|---|---|---|---|---|
| | | $ | Vol | LT | CO2 | Spill | | | |
| **1.1** | Environmental Monitoring and Oil spill preparedness | M | | | | H | 70% | B+ | Data availability, quality and cost related to data gathering (e.g. satellite data, airborne platforms). Organisational barriers. |
| **1.2** | Subsea Leak detection | L | | | | H | 80% | C+ | Requires cooperation between companies in order to develop new ML-based solutions and ensure an overall approach for leak detection. Trust in sensor technology. |
| **1.3** | Electrification of offshore installations | M | L | | H | | 80% | C/A** | Data ownership could still be a barrier especially for offshore wind application. |
| **2.1** | Seismic Processing | H | H | H | M | | 80% | A | No major barriers |
| **2.2** | Seismic Interpretation | H | H | H | L | | 100% | B+& C*** | Scaling requires that the data preparation process is streamlined and automated. New software solutions need to be developed and/or existing solutions taken into use. Broad implementation requires organizational change, e.g. ensuring that geologists are trained in new tools and new ways of working. |
| **2.3** | Well log interpretation | | H | M | L | | 100% | B+ | Data locked within the applications from software vendors. High diversity in data composite logs and formats. Large amount of image data results in high demand on computational power for graphic processing on ML model. |
| **2.4** | Increased Oil Recovery (IOR) | M | H | L | H | | 50% | C+ | Not fully developed, more research needed. Difficult to train models due to variations in reservoirs, installations and facilities. Reservoir models considered business critical and hence only a few are shared openly. |

* H,M,L not quantified. Key: **$**: Cost reduction; **Vol**: Increased production; **LT**: Reduced field development Lead time; **CO2**: Reduced GHG emissions; **Spill**: Reduced oil spills.
**Maturity Index: A**: ML scaled and adopted, **B**: Successful pilots, **C**: Idea and concept

** ML broadly applied for prediction of power from offshore wind

*** Facies interpretation, defining target reservoirs and geological models is still only in research

# The most promising ML applications for TTA 3 and 4

| TTA | ML application | ML Potential* | | | | | PoS full scale (A) | ML maturity Index | Main barrier for implementation of solution |
|---|---|---|---|---|---|---|---|---|---|
| | | $ | Vol | LT | CO2 | Spill | | | |
| **3.1** | Autonomous drilling and parameter optimisation | H | | L | M | | 80% | B+ | New way of working for drilling engineers to apply ML in well planning. Lack of trust in technology in particular for driller. Multiple suppliers applying different naming conventions for data. |
| **3.2** | Detection of downhole incidents | H | | L | M | | 90% | B+ | |
| **3.3** | Digital well planning | M | H | H | M | | 30% | C+ | Need access to other operator's overburden, pressure profile and experience data. New way of working for drilling engineers to apply ML in well planning. Multiple suppliers applying different naming conventions for data. |
| **3.4** | Drill fluid management | H | | H | M | | 10% | C | Low ML Maturity. |
| **4.1** | Predictive Maintenance & CBM | H | M | | M | | 50% | B+ | Data quality and sharing of data to develop viable degradation models for key equipment.<br>Lack of basic data-structure hindering comparison between assets. |
| **4.2** | Production optimisation | | H | | M | | 70% | B+ | Computational speed for large models – technology development needed for control room use.<br>Too high Initial investment cost for large on-line simulators vs business cases/benefits. |
| **4.3** | Logistics optimisation | M | | | H | | 10% | C | Co-operation between licences to share resources and data. |

* H,M,L not quantified. Key: **$**: Cost reduction; **Vol**: Increased production; **LT**: Reduced field development Lead time; **CO2**: Reduced GHG emissions; **Spill**: Reduced oil spills.
**Maturity Index: A**: ML scaled and adopted, **B**: Successful pilots, **C**: Idea and concept

# ML identified but not yet explored in the Norwegian Petroleum Industry

| TTA | ML opportunity | Problem definition |
|---|---|---|
| **3** | Service level prediction (maintenance) | Based on downhole tools' operational exposure, history of failures, MTBFs etc., ML algorithms can be used for service level prediction (maintenance requirement). May e.g. use historical failure data to optimize drilling parameters to avoid downhole tool failures. |
| **3** | Cuttings analysis | ML can be used for more accurate continuous analysis of cuttings by using visual technologies. |
| **4** | SIMOPS / Marine operations | Extraction of knowledge from past, similar Marine Operations as learning for the next campaign. By applying Natural Language Processing / ML applied for SIMOPS / Marine operations. |
| **4** | Unmanned platforms / autonomous production (ML, CBM, etc. is enablers for Unmanned) | ML learning can be used to minimize need for humans offshore through more advanced use of monitoring, censoring and robotics. |
| **4** | Automated field development, Standardized subsea satellites | ML is applied to automate FFED, EPC related activities. Requires sharing of information between operators and EPCI contractors. |
| **4** | Automated verification / compliance assurance | ML applied for automated verification / compliance assurance in FEED a detail engineering. |
| **4** | Design working process automation (machine thinking for design and procurement processes) | The design process has a lot of "waist" as information from one step to the next is not properly managed. New solutions like systematization of operator requirements, and standards requirements helps streamlining this process, and is well makes design changes, procurement more efficient. |
| **4** | Life extension / reuse of infrastructure | ML applied for life extension process by analyzing past history, history for similar assets, and projections to future operations.<br>Should be combined with classical RBI methods. |

# The added value from ML mostly comes in combination with other technologies

In the material collected, we see few cases where ML is used alone. Successful ML should be seen in combination with digitalisation èn-large as well as other technologies such as sensoring, systematic data collection, and other improvement actions within an enterprise.

**DIGITAL WORKER + SUPPORT**

Augmented reality

Digital worker

Expert centers / integrated operations


**INSPECTION AND DATA COLLECTION**

Mini-ROV

Drones

Sensors


**ANALYSIS**

Barrier panels, On-line risk

Pattern recognition

Data driven predictive maintenance

**ROBOTICS**

Unmanned remotely operated assets

Digitalization of requirements and specifications

3D-printing

**ML Applications: Hybrid solutions, deep learning, image processing, anomaly detection**

# 2 Machine Learning



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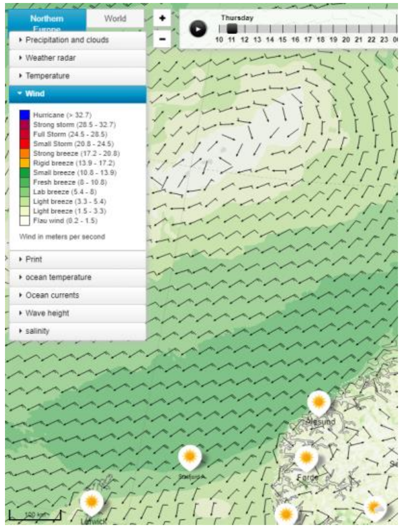
# Findings on the lesson learned during the development of ML solution

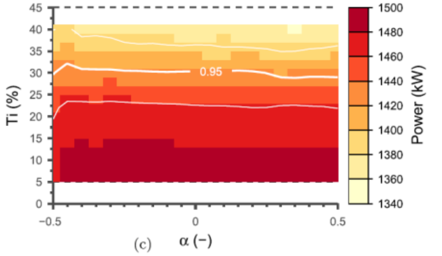
- **Criteria for successful of ML application (or adoption):**
  - well defined ML problem, frame the ML problem in the right context .
  - well defined strategy, where ML can add value to the problem.
- **When to use ML?**
  - When we do <u>not</u> have a good deterministic model.
  - It is a repeat problem.
  - The data is representative for the future in sufficient quality and quantity.
- **Physics based simulator** could be used as final test to see the performance of ML application.
- **Physics based model** in a *hybrid model* with ML solution is **useful for**:
  - reduce false positive (ML result uncertainty)
  - increase time to respond
  - constraint the ML so it behaves according to physics understanding
- **Holy grail of ML**: encode physical representation into the ML algorithm. This is front end R&D not available for practical use yet.

## Example of Hybrid Solution




Source: www.yr.no

Using physical based modelling to predict atmospheric parameters




Source: Clifton et. Al. (2013)

Using machine learning to predict wind turbine power output based on the input of atmospheric parameters from the simulation.



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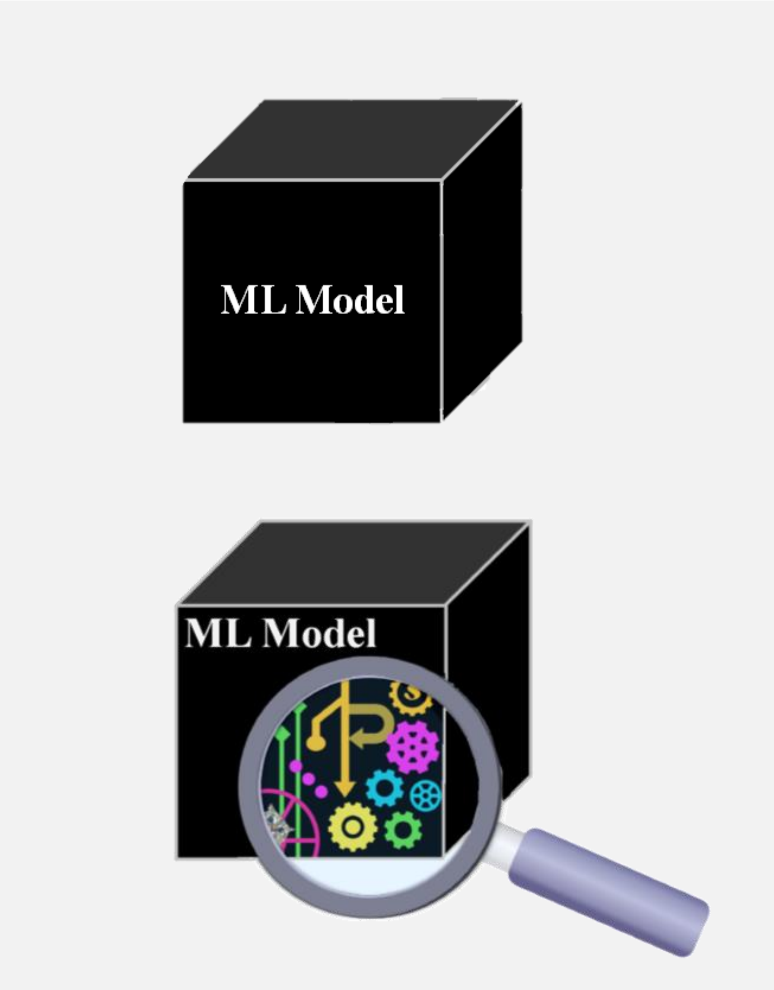
# Findings on the lesson learned during the operation of ML solution

- We observe **unanimous position** with regards to the application of ML in industrial context:
  - ML should not be a stand alone solution, i.e. **hybrid solution** is preferred.
  - ML should be made **less black box**, i.e. it should be possible to interpret, verify and explain.
  - Any stakeholder involve in the planning, development and operation of ML application should be aware of its **strengths, weakness and limitations**.
- **Hybrid solution** may have several meanings or implications:
  - ML is applied on top of or in cooperation with first-based principle (or physics based) models/algorithms.
  - ML application for safety critical system should only be limited as decision support system, i.e. people is always in the loop.
- One of ML **limitations** for its widely adoption is related to **scalability**, i.e. a success for one case is not necessarily easy and straight forward to implement it to other systems.



# The 3 main types of machine learning

**Supervised learning**
deals with labeled training data. So in the training data we have both the input and the output. The goal of supervised learning is to obtain a predictor, such that when new input given, can predict the output.

1

**Unsupervised learning**
deals with unlabeled data. We only have input data. The goal of unsupervised learning is to obtain the hidden patterns to learn about the data.

2

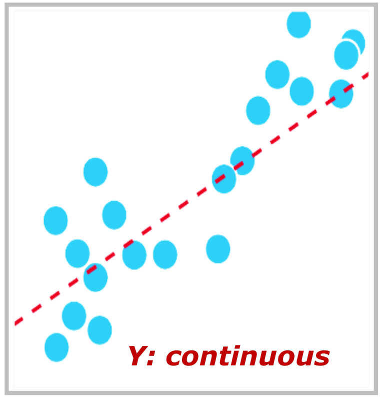
**Reinforcement learning**
concerns with how an agent ought to take actions in an environment, that is learning what to do—how to map situations to actions—so as to maximize a numerical reward.

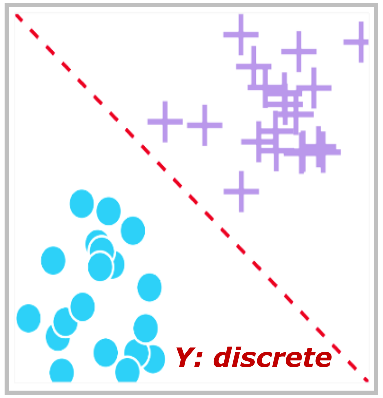
3

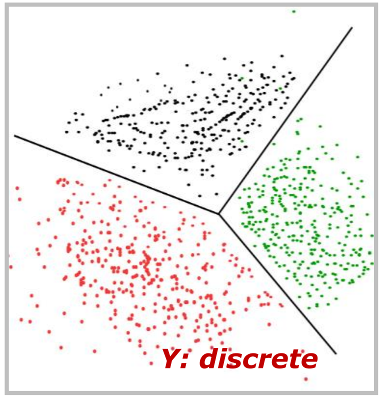
# Machine Learning Types

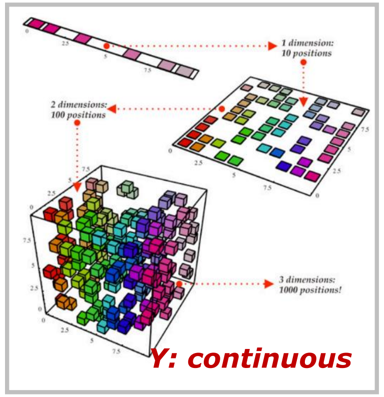
INPUT **X** → PREDICTOR F(**X**) → PREDICTION **Y**

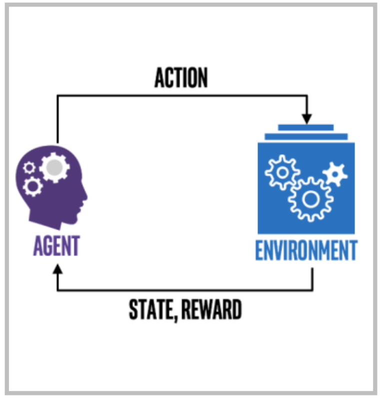
- **Machine Learning**
  - **Supervised Learning**
    - **Regression**
    - **Classification**
  - **Unsupervised Learning**
    - **Clustering**
    - **Dimensional Reduction**
  - **Reinforcement Learning**




**See next slides for examples on ML application for Norwegian Petroleum Industry.**



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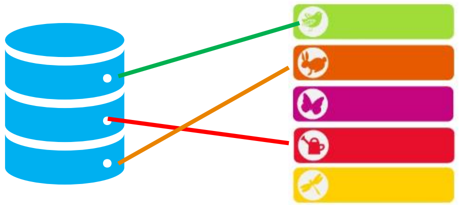
# Example use of different types of ML

| Domain | Problem | Example use and ML type* |
|---|---|---|
| **TTA 4**: Anomaly detection on rotating equipment | Not sufficient time from warning to failure of equipment and lack of data from real failure cases as machinery is protected to avoid failures. | **Anomaly detection**<br>**Step 1: Unsupervised clustering ML type**<br>**Step 2: Annotation**<br>**Step 3: Supervised classification ML type**<br>▪ ML is used to determine what is normal (Unsupervised clustering) as opposed to what is an unwanted outcome (equipment failure or stuck pipe). ML model built through annotation (labelling) of the normal states.<br>▪ ML predicts what comes next based on ML model providing warning on deviation from normal (supervised classification) |
| **TTA 3**: Detection of downhole incidents | Detecting and avoiding drilling incidents like downhole vibrations, twist off, stuck pipe, kick detection, Torque & Drag etc. | |
| **TTA 4**: Predictive maintenance - Remaining useful life | In this case data from real case failures are required and time series with data leading up to the failure is important. | **Prediction through supervised regression ML type**<br>Neural network is built based on time series data from operation including failure data with pattern to data prior to failure. The ML model search for degradation pattern in order to estimate the remaining life. |
| **TTA 4**: Production optimization - Virtual flow meter | Instead of using expensive hardware metering devices, numerical models are used to compute the flowrates by using readily available field measurements such as pressure and temperature.<br>For economic operation of the production systems, it is important to know the oil, gas and water flowrates from each well. It allows operators to make critical decisions in production optimization, rate allocation, reservoir management and predict the future performance of the field. | **Optimization**<br>**Step 1: Build and test unsupervised dimensional reduction ML type model**<br>**Step 2: Build and test supervised regression ML type model**<br>**Step 3: Compare results first principle (Hybrid solution)**<br>Dimensional reduction algorithms (unsupervised learning) can be used in pre-processing step to construct informative features, find complex relationships between the original data and the output variable and remove redundant features.<br>Historical time series data (temperature, pressure, fluid properties, operation conditions) from different wells with hardware metering devices are used to construct a supervised ML model (outcome is known). The outcome from the test of the ML model is recommended to be compared with the outcome from a first principle model for validation in particular for extreme cases. |
| **TTA 2**: Seismic interpretation | E.g. fault and horizon interpretation | **Step 1: Manual classification or unsupervised clustering ML type**<br>**Step 2: Annotation**<br>**Step 3: Supervised classification ML type**<br>First step is to cluster geological features either manually or by applying an unsupervised clustering ML type. Second step is annotation (labelling) of the geological features with subsequent construction of a supervised ML classification model. The end results will a ML model being able to identify faults and horizons. |

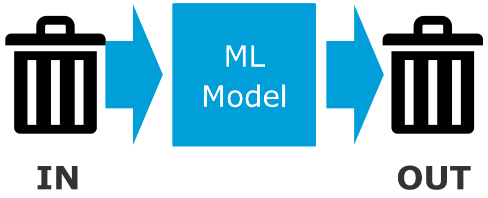
* Not a complete list of required steps and processes for ML adoption

# Some Machine Learning Limitations

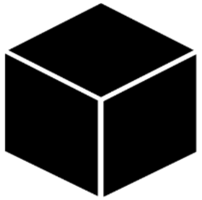
ML algorithms require massive amount of training data.



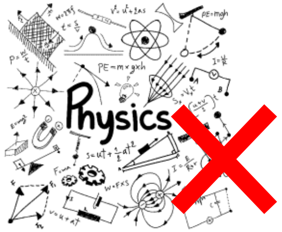
Supervised learning requires labelled data and labelling training data is a tedious process.



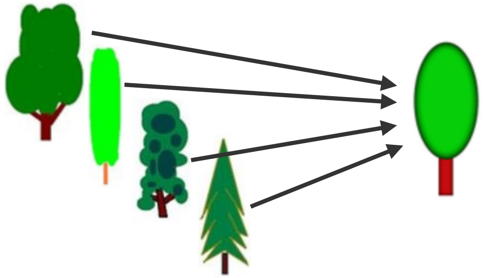

Any bias and DQ issues in the data will be reflected in the prediction results.



Blackbox: the results of some ML models are hard to be interpreted and how the models came to the decision are difficult to explain.




ML algorithms do not understand physics laws.



ML models still lack the ability to generalize conditions.

# Risks related to the application of ML solutions

- **Does the ML technology work as expected and how would we know**? We are creating complex systems and these systems have embedded risks which are different from the sum of their parts. This can lead to emerging risks and, consequently, new trust gaps. We ask ourselves: **How can we build trust in such new technologies**?
- **A high-risk scenario reduces the tolerance for erroneous predictions.** We cannot accept a decision, that may have catastrophic consequences being based on faulty predictions of an ML algorithm or AI agent.
- **Critical consequences are often related to tail events - for which data are naturally scarce.** ML methods require data. If the training data are scarce, the uncertainty associated with the predictions will be high, and the predictive accuracy significantly reduced.
- **ML models that are able to fit complex data well are often opaque and impenetrable for human understanding.** This makes the model inscrutable and less falsifiable. For a decision maker in a high-risk context, this increases the uncertainty and thus reduces her ability to trust the model.
- Example of high risk application
  - Prediction of load bearing structural failures



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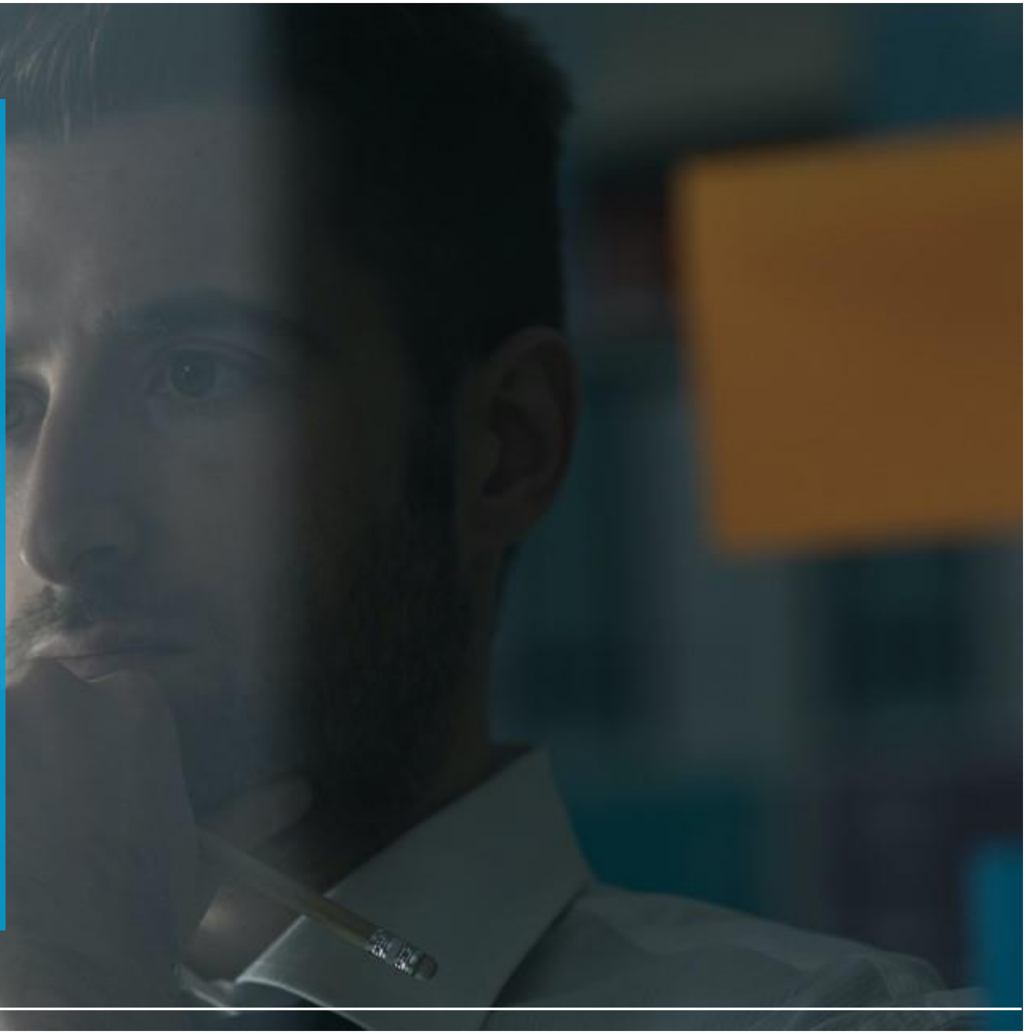
# Some important checklist items for success with machine learning



1. Is the problem well defined, repeated and represent an important problem to be solved?
   a) Is there a business case for solving the problem? Can a success be scaled and broadly implemented to magnify the value? Are all factors for full implementation (e.g. new tools, new competency requirements, training requirements) accounted for in the business case?
   b) Is there good and validated "Non-ML" solutions available for the problem? If yes, use them.
   c) Otherwise ML could be considered.
2. Determine suitability of ML, especially related to data with sufficient quality and predictive power.
3. Involvement of domain experts in building the ML model.
4. Validation and testing confirms ML performance and it brings value with acceptable risk.
5. Is the operational environment allowing you to easily retrain and redeploy the model?
6. Peer review and verification of ML model and the development process successfully implemented.

A more comprehensive checklist and guidance can be found in DNV GL RP 0510.

# What do we mean by a hybrid solution combining ML and first principle?

**Example of combining ML and first principle (hybrid)**

- A physical model (E.g. Computational fluid dynamics or finite element analysis) is run to create synthetic training data as input for building a ML model. The advantage of this is that the ML model will provide faster results compared to physical simulation tools. The ML model may however have a lower accuracy compared to the output from the physical simulation tools.
- When you build the ML model you can force the ML model to be constrained and behave according to physics understanding.
- There are multiple R&D efforts to encode physical representation into the ML algorithm. This is front end R&D not available for practical use yet.

References:

Combining machine learning and process engineering physics towards enhanced accuracy and explainability of data-driven models Timur Bikmukhametov* , Johannes Jäschke, April 2020.

DNV GL: https://ai-and-safety.dnvgl.com/

# Why do we need Hybrid Solutions?

## How it combines the best of both worlds*

| | Data driven modelling (ML) | Physics simulations | Hybrid solution |
|---|---|---|---|
| **Strengths** | + Fast inference<br>+ Reveals hidden patterns in the data<br>+ Strong capability to relearn from new data<br>+ No prior assumption required for the process | + Generalizable<br>+ Proven accuracy with known limitations<br>+ Explainable predictions | + Fast inference<br>+ Generalizable<br>+ Proven accuracy with known limitations<br>+ Explainable predictions |
| **Weaknesses** | ÷ Often more difficult to explain outcome<br>÷ Highly depending on good data quality<br>÷ Difficult to make ML model generalizable | ÷ Slow predictions<br>÷ Expensive to develop<br>÷ Limited to current physical understanding<br>÷ Less adaptive to learning | |

* This slide is inspired and further developed based on "Hybrid AI/ML- Bridging the gap between machine learning and real assets, Shane McArdle, Vice President Kongsberg Digital AS, 26. august 2020

# 3 Detailed TTA study results

# 3.1 TTA1 – Energy efficiency and environment

# TTA1 – Energy efficiency and environment: Several areas were explored, and 3 areas were identified as high potential

| Integrated monitoring/modelling and Oil spill preparedness | Subsea leak detection | Electrification of offshore installations |
| --- | --- | --- |

Other areas that were mapped and explored:

**Carbon capture and storage**

**Produced water management for EOR chemicals**



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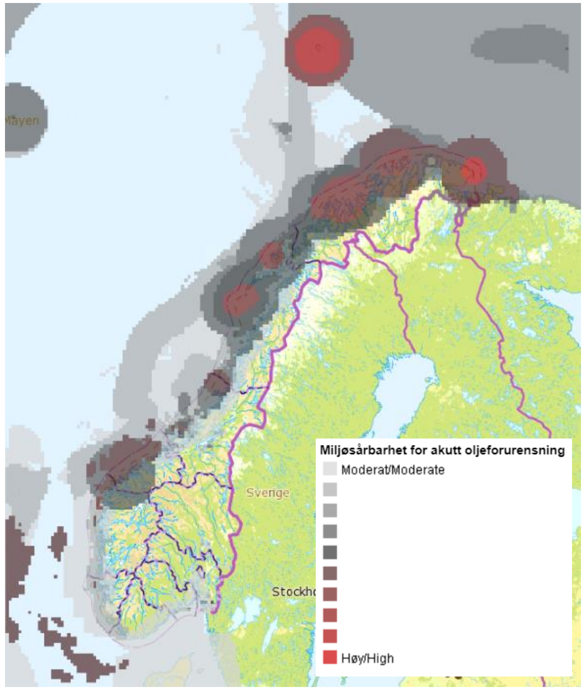
# TTA1.1: Integrated monitoring/modelling and Oil spill preparedness




Environmental vulnerability towards oil spill pollution (Havmiljo.no)

**Challenge**

Increased attention from authorities coupled with entrance into remote and sensitive areas requires new solutions for environmental risk management.

- Need improved understanding of natural variations of the ecology in question
- Need to ensure ability of early detection and sufficient response time of oil spill events or other possible events impacting the environment

The industry agree on the need to develop solutions for real time monitoring and improved systems for remote sensing.

**Opportunity**

- ML applied can enable higher resolution monitoring that will give an improved understanding of natural variations.
- ML could be used to identify correct measure for the particular response operation, combining ecological and physical data.
- ML can enable faster characterisation of oil spill based on satellite imaging.
- ML can enable real time monitoring for operations (e.g. drill cutting disposal) to facilitate decisions involving environmental risk.

**Benefit for the O&G industry**

- ML is regarded as a critical component for development of environmental management system enabling possible entrance in sensitive and remote areas.
- Correct decision preventing environmental damage in operations can save substantial costs related to possible clean up activity.

**Status:**

Machine Learning is part of some of the solutions today, both with respect to environmental monitoring and oil spill preparedness. However, significant improvements are still needed to realize the full potential of ML.

**Barriers for ML:**

- Data availability for environmental purposes
- Different disciplines and actors involved
- Quality and cost of satellite data
- Data sources and costs related (spec. airborn platforms)

**Enablers:**

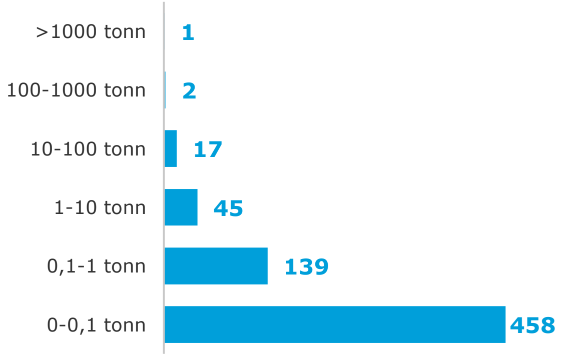
- Development of unmanned platforms drives new solutions
- Strong focus from authorities
- Data sharing and cooperation among operators and other actors are established
- ML is already being used in different applications; hence experience is gained.

**Risks:**

- Wrong prediction of environmental impact leading to costly and misguided measures

# TTA1.2: Subsea leak detection

**Incidents with acute oil spill 2001-2018**
Divided on leakage categories (Ptil 2018)




**Incidents with acute chemical spill 2001-2018**
Divided on leakage categories (Ptil 2018)


## Challenge

Increased attention from authorities coupled with an increase in subsea activities in the years to come forces the industry to develop new solutions for subsea leak detection.

- Need to develop solution that is not stand alone but is integrated in a more holistic solution for detection and response.
- In particular, the industry needs solutions for detection of small leakages and reduce the challenge of false alarms.

The industry need to develop new solutions based both on existing systems and new technologies.

## Opportunity

- ML can be applied as part of existing systems for leakage detection (e.g. mass balance) in order to improve sensitivity of the system and hence detect small leakages before they occur.
- ML could be used as part of an integrated system for detection of leakage, with several technologies and data sources involved (e.g. subsea sensors and remote sensing).

## Benefit for the O&G industry

- ML is regarded as an important component in improving existing mass balance systems to detect small leakages. Small leakages is by far the most frequent event when it comes to oil spill, however also the most difficult to detect. Detection of such spill will not only reduce environmental impact from the leakage itself but could also prevent larger leakages to occur.
- ML could save cost due to reduced need for additional sensors and potential for false alarms.

## Status:

The most promising application in near time lies in adding ML to already existing systems as mass balance. This is most cost effective and ML would be able to adjust to changing production profiles over time. Subsea sensoring is costly but is regarded to be part of the future solution for subsea leak detection.

## Barriers for ML:

- Development of solutions require cooperation
- Trust in technologies might be a barrier for further development

## Enablers:

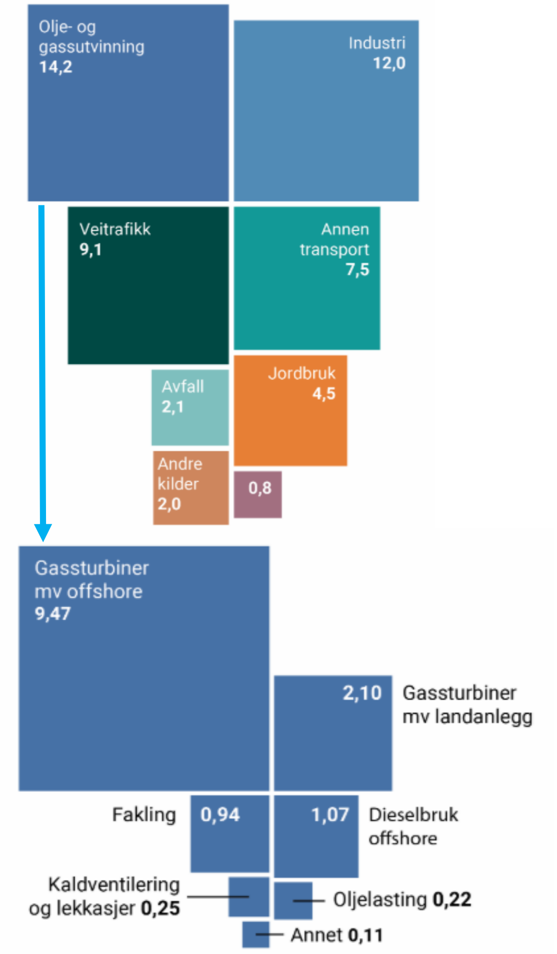
- Development of unmanned platforms drives new solutions
- Strong focus from authorities – both Petroleum Safety Authorities and Norwegian Environmental Agency

## Risks:

- If the algorithms does not manage to detect a leakage it could cause negative environmental impact

# TTA1.3: Electrification of offshore installations

**Mt. CO2 equivalents**




GHG emission 2018 in Mt. CO2 equivalent (Miljøstatus, Mdir)

| | |
|---|---|
| **Challenge** | The oil and gas industry has committed to $CO_2$ reduction targets:<br>▪ -40% in 2030 compared with 2005<br>▪ Near zero in 2050<br>Significant cuts need to be taken on existing and new assets on the NCS. |
| **Opportunity** | ▪ ML can be part of solutions for electrification of assets on the NCS, both within Power from shore technologies and Integration of offshore wind.<br>▪ ML is vital for prediction of power from offshore wind installations and hence to ensure an efficient operation of an integrated management system.<br>▪ ML could possibly contribute with necessary cost reduction by reducing conservatism in design, optimize over the lifetime of the windfarm.<br>▪ ML could be used as part of an integrated management system for an offshore power-hub balancing demand and supply. |
| **Benefit for the O&G industry** | ▪ Power from shore is assessed to have a potential to reduce $CO_2$ emission from upstream activities with 85% (Rystad 2019).<br>▪ Integration of offshore wind is assessed to potentially reduce $CO_2$ emissions with 35-40% per installation (Rystad 2019).<br>▪ Power prediction from wind turbines together with back-up solutions is challenging, and ML solutions can play a role. |

**Electrification and ML:**

Machine learning is part of solution both when it comes to preventive maintenance of wind turbines (resulting in already high uptime) and for power production prediction. Challenge is now to develop this further in order to meet requirements for feeding into an offshore facility grid. This implies better time resolution and more detailed forecast confidence.

**Barriers for ML:**

- Ownership of data is still an issue; however this barrier was more dominant some years ago.

**Enablers:**

- Already existing use of ML in the wind industry in general is an enabler for use of ML for offshore wind power of NCS.
- Fleets of wind turbines provide a lot of data that can be used for ML application.

**Risks:**

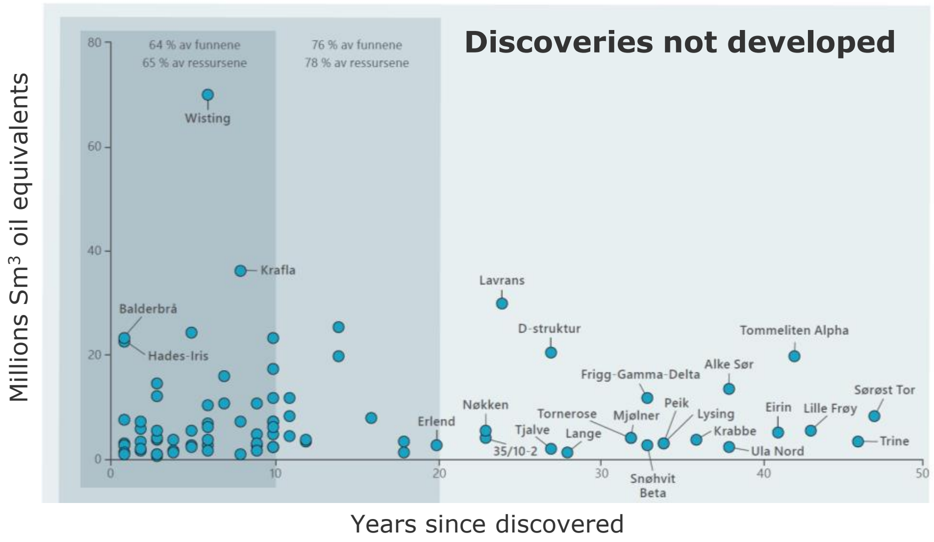
- Wrong power demand/supply balance could lead to power fall out or in-efficient operation of back up solutions.

# 3.2 TTA2 – Exploration and improved recovery

# NS «average» Field Development Schedule

Licence Award — 6 years — Discovery — 10 years — PDO — 3 years — First oil — 1-80 years

| Open acreage Exploration | Licensed Exploration | Pre-PDO field development decision gates | Execution | Production |
|---|---|---|---|---|
| ML on; seismic processing and interpretation, missed pay, well data structuring and contextualization | ML on seismic<br>Reservoir characterization | Uncertainty studies<br>Ensemble simulation<br>Optimization strategy<br>Speed up modelling | Well design<br>Geo steering<br>Optimize well trajectories<br>Geomechanics ERD | ▪ Big data & huge opportunities for ML<br>▪ History matching<br>▪ Fast model update<br>▪ Geomechanics ERD<br>▪ Production optimization |

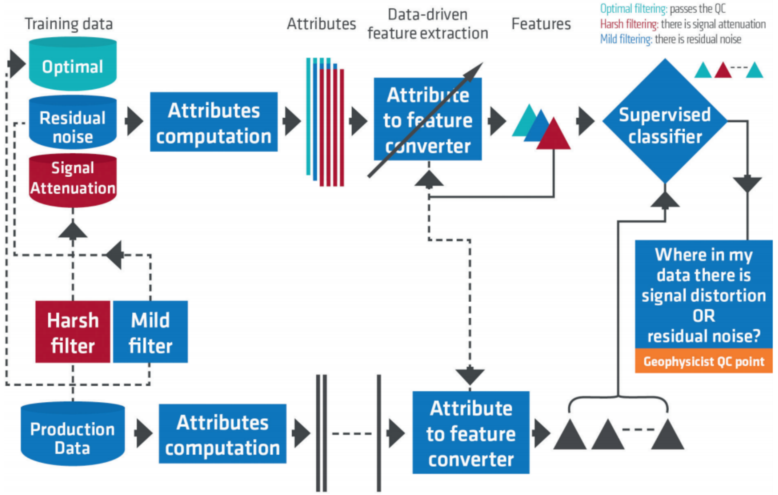



*Stanford University project has concluded; ML has a good potential onshore with many similar fields. Field development in the North Sea is however hampered by a more complex infrastructure and requiring many agreements to be executed making it more difficult to copy the ML success from onshore field development.*

Largest potential for ML

# TTA2.1: ML – Seismic Processing

## QC in Seismic Data Processing




## Cost versus year of acquisition for 3D seismic data in the North Sea, UK

| Year | K USD/km² | |
|---|---|---|
| 1982 | 70-100 | |
| 1986 | 30 | |
| 1990 | 12-15 | |
| 1993 | 8-9 | |
| 1999 | 4 | |
| 2002 | 10-20 | |
| 2007MC | Pre lic. 1,65 | After 5 |

https://mem.lyellcollection.org/content/memoirs/29/1/1.full.pdf
https://expronews.com/exploration/the-rise-of-multi-client-data-new-business-models/

| | |
|---|---|
| **Challenge** | Too long from time from acquisition to interpretable seismic. Traditional manual seismic processing means extensive man-hours.<br>From a seismic processing and imaging perspective, ML applications include:<br>1. Noise attenuation<br>2. Velocity model building (VMB)<br>3. Signal reconstruction<br>4. Optimization of parameters used in seismic imaging<br>5. 4D seismic processing in producing fields takes too long |
| **Opportunity** | ▪ Noise removal traditionally done on a few test lines can be done on the whole survey using ML, faster and better.<br>▪ Experienced geophysicist is needed for velocity picking, ML has the function of trial and error on large datasets.<br>▪ ML on seismic imaging has been tested successfully. |
| **Benefit for the O&G industry** | ▪ Better seismic will result in less dry wells.<br>▪ 4D seismic for infill production wells need to be delivered fast to identify bypassed oil and good targets for drilling.<br>▪ Cost of 3D is not so simple anymore, MC business model and size matters more.<br>▪ Currently seismic companies take risks shooting seismic speculative and not on contract to cover the full cost. ML cost reductions related to seismic processing, will be for the seismic companies mainly. |

### ML on Seismic:

2D and particular 3D and 4D seismic are huge datasets, which recently has opened a new era of seismic imaging enhanced by ML. Adoption of ML is seismic processing is today broadly implemented.

### Barriers for ML:

- Seismic companies have basically no barriers for adopting ML on seismic
- Oil price fluctuations are resulting is a challenge for long term ML development

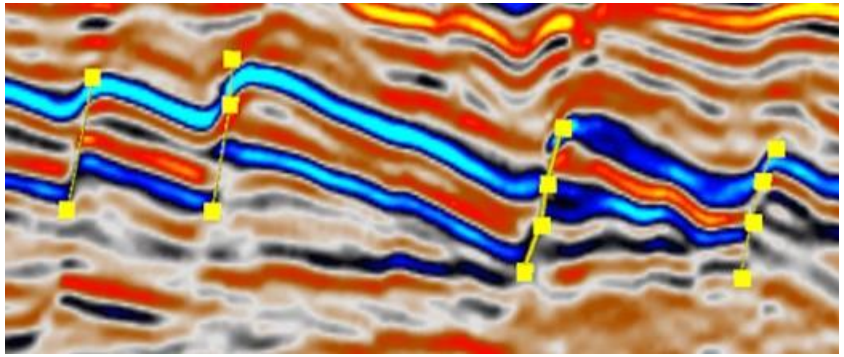
### Enablers:

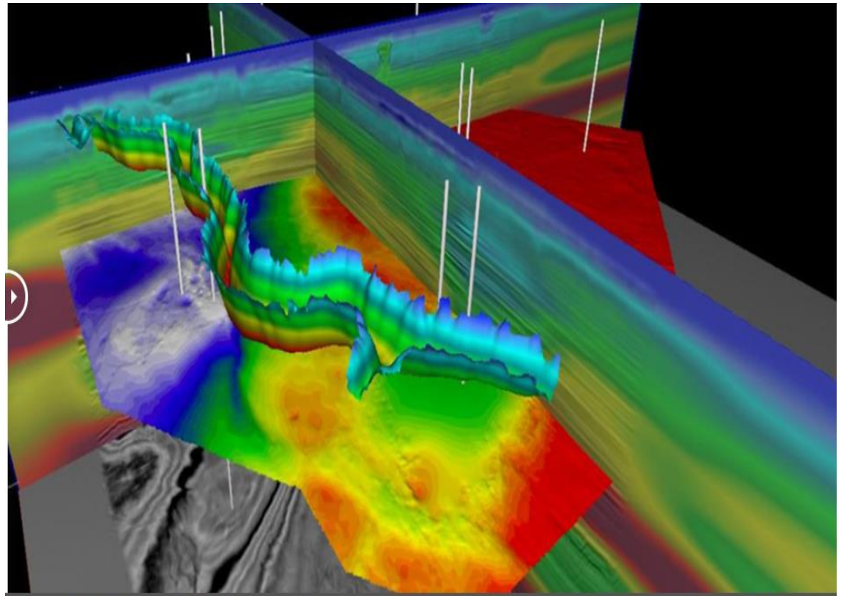
- Computing power

### Risks:

- No significant risks

# TTA2.2: ML – Seismic Interpretation





Co-rendered FWI model on seismic data with extracted velocities shown in one channel system. Slide the bar to compare two images. The image on the left, without FWI, shows the channel imprint on extracted amplitudes below the channel. In the image on the right this imprint has been removed using the FWI model.

| | |
|---|---|
| **Challenge** | Time spent on repetitive work is too long. More time should be spent on creative valuable work. Fast Model Update (FMU) requires fast results in 3D and 4D.<br>1. Fault interpretation (exploration and production), has come very far and is now in production.<br>2. Horizon interpretation (exploration and production) in FMU context is now in production.<br>3. ML adoption for seismic interpretation in exploration is still immature.<br>4. Facies interpretation, defining target reservoirs and geological models is still only in research. |
| **Opportunity** | ▪ Faster turnaround from finished processed seismic to creative seismic interpretation. |
| **Benefit for the O&G industry** | Benefit case 1: From 1 week to one day for seismic interpretation through application of ML.<br>▪ Expected 100-150MNOK yearly savings within exploration interpretation.<br>▪ Similar benefit expected in IOR 100-150MNOK per year.<br><br>Benefit case 2: Certain processes is done in 1/10 of the time using ML.<br>▪ More Geological and reservoir information out of seismic. |

**Status:**

During 5 years of ML in oil & gas, significant leaps of increased efficiency but more investment and development are needed to move technology forward.

**Barriers for ML:**

- Interpreters need to be trained for the new tool
- New software on seismic interpretation is competing with existing widespread software where data is inherent.

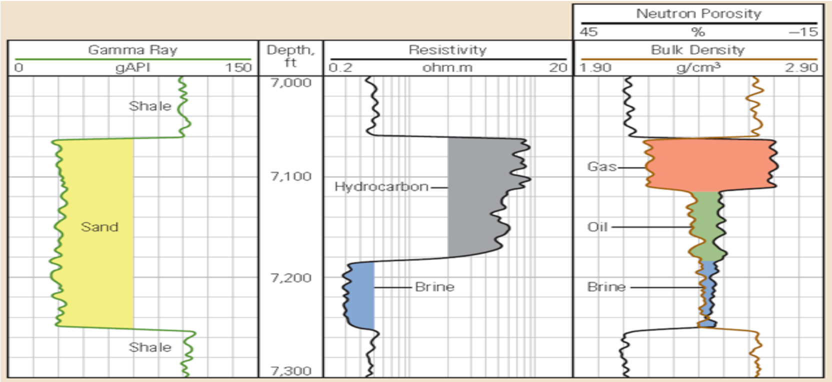
**Enablers:**

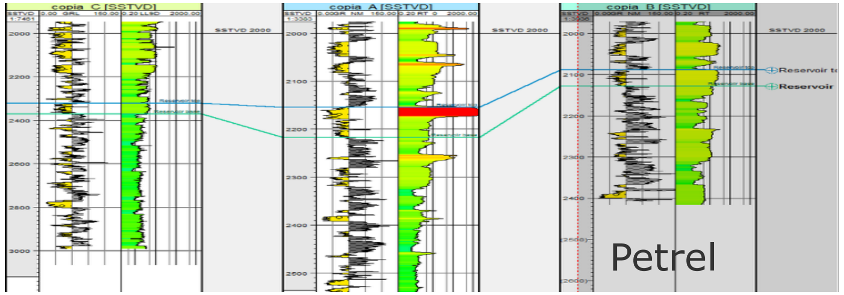
- Research and competence building

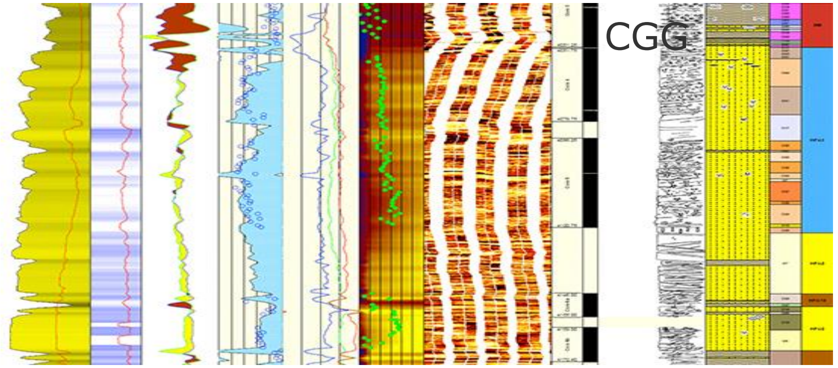
**Risks:**

- No significant risks

# TTA2.3: ML – Well log interpretation




## Challenge

Well data is unstructured, stored in silos, representing versions not always corrected for depth and environment.

1. Petrophysics auto correction, auto interpretation and store in "the cloud".
2. Well data is usually on pdf, tiff, and excel, LAS, DLIS, images and tabulated results, and endless versions.
3. Huge amounts of scanned copies to be organized and searchable, (not so much in Norway).

## Opportunity

- Petrophysics on a grand scale in fields of say 150 wells can be reinterpreted in days rather than months.
- ML can make unstructured data structured.

## Benefit for the O&G industry

- Efficiency in data QC and management
- Enables missed pay
- Less man-hours

## ML on Well Data Management:

Some examples of successful application of ML in oil & gas and increased efficiency.

## Barriers for ML:

- Software vendors tend to keep data within application
- QC of data is a challenge; to be sorted by ML:
- Diskos not configured for ML, but could be transferred to a cloud store for ML application

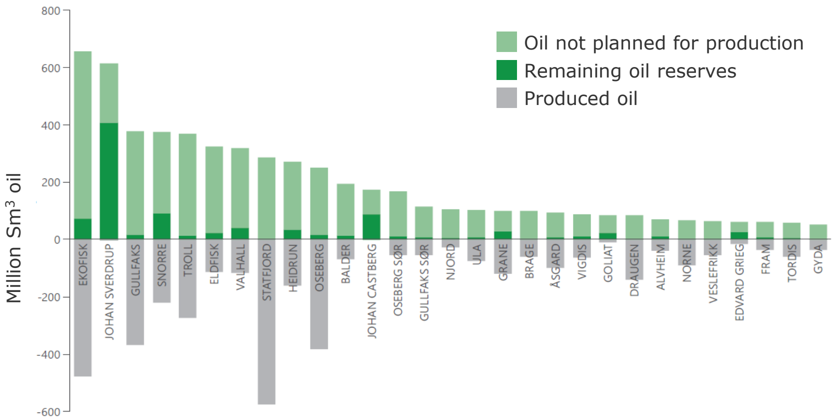
## Enablers:

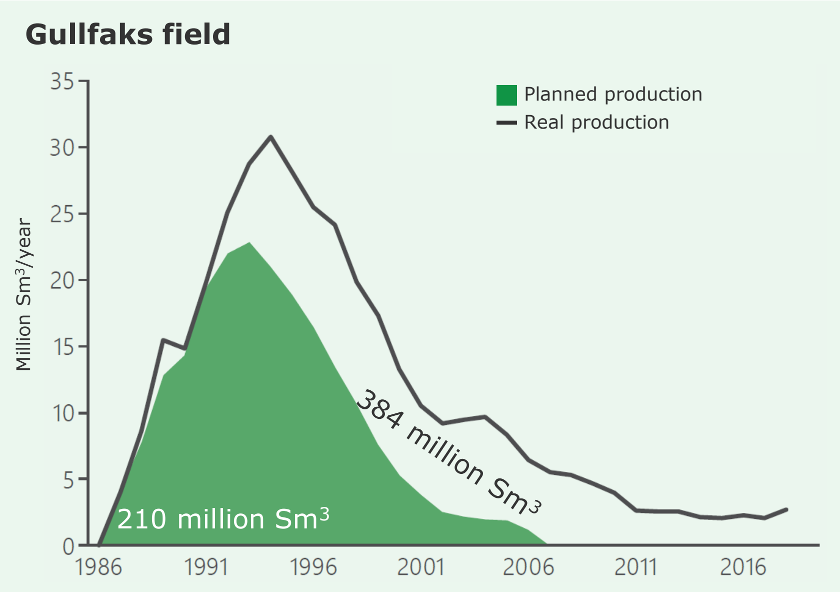
- Many companies are offering these services

## Risks:

- No significant risks

# TTA2.4: ML – Increased Recovery




## Challenge

In producing fields large amounts of data is acquired, bbl/day per well, per zone. Numerous sensors are presenting a complex and sometimes not very confident picture. Allocation challenges, choking and re-perforations, as well as closing off watered intervals.

1. Platform operators are making decisions on how to optimize well flow.
2. Reservoir engineers are evaluating a huge flow of data, well stream allocations, history matching, prognosticate future production and plan for interventions.

## Opportunity

- ML; By learning of the past actions, production management can be optimized.
- Reduced history matching time and effort from months to weeks.
- ML provides unbiased results.
- In new (and old) fields massive data acquisition programs provides extensive databases and open new level of understanding using ML

## Benefit for the O&G industry

- Increased recovery
- Reduced time and effort for history matching

**ML in IOR:**

1. Immature
2. Huge potential for increased oil recovery

**Barriers for ML:**

- Lack of trust in ML models
- Training of models and competence building
- Difficult to train models due to variations in reservoirs, installations and facilities
- Data sharing. Reservoir models are often seen as more business critical and hence only a few are shared openly.

**Enablers:**

- Extensive data available for ML

**Risks:**

- No significant risks

# 3.3 TTA3 – Drilling, completion and intervention

# The way towards fully autonomous drilling

Autonomous drilling is at an early stage with some use of ML embedded within the drilling controls. Control of drilling parameters can be done fully automatic today but level of implementation is limited. Robotics for drill floor operations also being developed but is generally more complex and contribution from ML is more limited.

**Incident detection**

**Autonomous drilling**

**Autonomous drilling with robotics on drill floor**

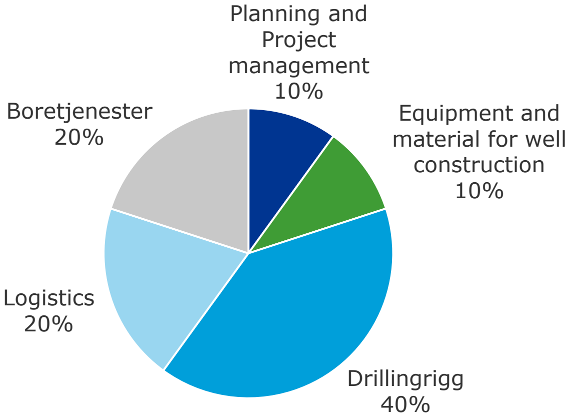
**Benefits:**

- Improved drilling efficiency
- Performed within technical limits every time
- Reduced operational cost
- Improved safety for rig floor personnel

# TTA3.1: Autonomous drilling and parameter optimisation

## Drilling cost (MNOK/well)


## Distribution of drilling cost




Source: KonKraft presentation, "Brønnleveranser for fremtiden", Per Lund, 5th February 2018

| | |
|---|---|
| **Challenge** | ▪ 35-50% of a well's cost is related to drilling and completion of the well over the lifetime of the well. (Konkraft 2018).<br>▪ Cost savings may be achieved through increased drilling speed (Forskningsrådet 2020). |
| **Opportunity** | ▪ Optimising the drilling parameters using ML, results in increased ROP and more efficient flat time, which again reduces average time spent per well. ML can be used for qualified decision, either automatic or manual, during drilling to increase drilling efficiency. This reduces average time spent per well. |
| **Benefit for the O&G industry** | ▪ Ensuring operating within well and equipment's limitations<br>▪ Enhanced drilling operation efficiency<br>▪ Leads to increased volumes as the economy in marginal wells improve<br>▪ Reduction in invisible lost time (ILT)<br>▪ Up to 12% increased efficiency observed<br>▪ Potential to reduce well delivery time and cost by 30-50% compared to conventional drilling technology (Forskningsrådet 2020) |

**D&W and ML:**

ML is an important part of current commercial software and solutions for autonomous drilling, but its full potential is not yet currently exploited. The main barrier for scaling and broad implementation has been identified to be lack of trust in following any advice provided by the ML models.

**Barriers for ML:**

- New way of working for drilling engineers to apply ML in well planning.
- Lack of trust in technology in particular for driller.
- Multiple suppliers applying different naming conventions for data.

**Enablers:**

- Sharing of ML software, tools and models
- New generation drilling engineers with more data centric skills

**Risks:**

- Wrong prediction (too conservative or too aggressive). Lost circulation situation leading to loss of primary barrier (drilling fluid) and loss of time to re-establish barrier.
- Reduced operating window



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# TTA3.2: Detection of downhole incidents

**2017 Semi-sub & jack up development well cost breakdown**

**2017 Platform development well cost breakdown**

- Cement & Mud
- Equipment & Casing
- Logistics
- Rig Cost
- Services & Rental
- Time Writing & Overheads
- Waiting on Weather
- Non-productive Time

Source: Wells Insight Report 2018, Oil & Gas Authority

| | |
|---|---|
| **Challenge** | ▪ Non-productive time (NPT) makes up around 15-25% of the well cost (Konkraft).<br>▪ Cost savings may be achieved through reduced non-productive time (Forskningsrådet 2020). |
| **Opportunity** | ▪ ML can be used for detecting drilling incidents (anomalies) like downhole vibrations, twist off, stuck pipe, losses, kick detection, Torque & Drag etc..<br>▪ This can be done by monitoring and trend analysis of real-time data. |
| **Benefit for the O&G industry** | ▪ Reduction in NPT – potentially 50% reduction by using new or improved technologies (OG21)<br>▪ Circa 20% less sidetracks |

**D&W and ML:**

Machine Learning is used for monitoring and trend analysis of real-time data today, to detect downhole incidents and alarm the driller in due time of any events. However, the full potential of ML is not realized.

**Barriers for ML:**

- New way of working for drilling engineers to apply ML in well planning.
- Lack of trust in technology in particular for driller.
- Multiple suppliers applying different naming conventions for data. Time stamp data applied differently amongst suppliers.

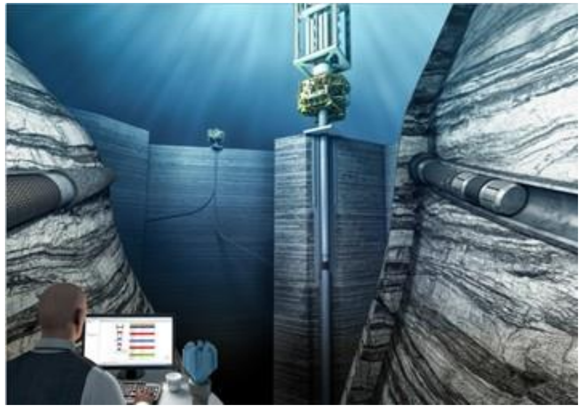
**Enablers:**

- Sharing of ML software, tools and models
- New generation drilling engineers with more data centric skills

**Risks:**

- Wrong prediction (too conservative or too aggressive). Unnecessary time spent on troubleshooting.

# TTA3.3: Digital well planning



| | |
|---|---|
| **Challenge** | ▪ Typical time spent on well designing work is 2-3 months.<br>▪ Cost savings may be achieved through reduced non-productive time (Forskningsrådet 2020).<br>▪ Reduce time spent on well design, optimize well design, reduce ILT and NPT. |
| **Opportunity** | ▪ Automatic well path and well design based on historical and experience data.<br>▪ Reduce time spent on well design, optimize well design, reduce ILT and NPT. |
| **Benefit for the O&G industry** | ▪ A more agile well design process, closer to real-time well planning with up to 80% decrease in well designing time.<br>▪ Possibly higher well success rate leading to the production goal is met.<br>▪ Increased production due to optimized well design (maximized reservoir contact).<br>▪ Avoid requirement to drill additional well due to poor well design.<br>▪ Enabler for better drilling thorough real-time update of plans. |

**D&W and ML:**

Some pilots conducted for digital well planning. This is an area requiring significant effort and time today and ML has a large potential to streamline and shorten the time and effort in the digital well planning process.

**Barriers for ML:**

- Need access to other operator's overburden, pressure profile and experience data.
- New way of working for drilling engineers to apply ML in well planning.
- Multiple suppliers applying different naming conventions for data. Time stamp data applied differently amongst suppliers.

**Enablers:**

- Sharing of ML software, tools and models
- New generation drilling engineers with more data centric skills
- Data sharing for small operators with limited experience and data sets

**Risks:**

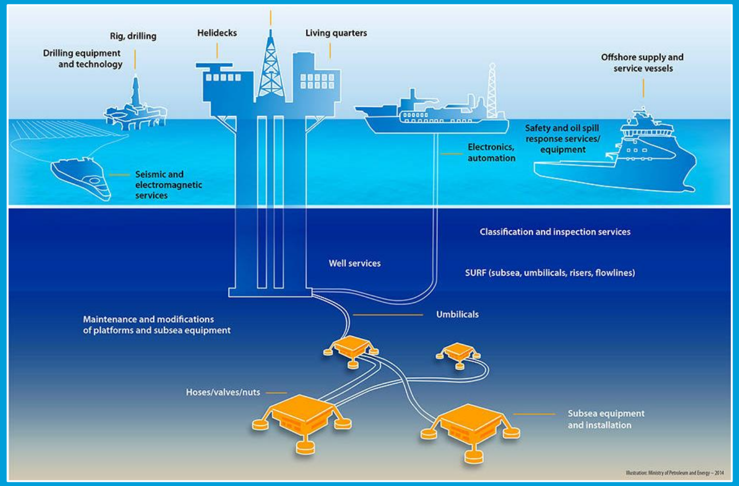
- Engineering experience is critical to quality check the well design and planning algorithms

# Drilling fluid management and mixing

| | |
|---|---|
| **Challenge** | ▪ Drilling fluid mixing is manual work and opens for human error. |
| **Opportunity** | ▪ Efficient drilling fluid management and mixing resulting in tailor made and optimized drilling fluid for a specific well. |

| Key technologies | Gain/value | Maturity | Potential saving | Barriers |
|---|---|---|---|---|
| Drilling fluid management and mixing | ▪ Optimization of mud design.<br>▪ Tailor made fluid for the well while drilling.<br>▪ Mud specification is kept within the acceptance criteria and at the same time ensuring the required qualities of fluid is maintained.<br>▪ Predict fluid properties as function of additives; partly unknown starting point; learn during operation. | C | ▪ Reduced cost due to less personnel offshore<br>▪ Less HSE incidents due to less personnel offshore<br>▪ Reduced NPT | ▪ Time/depth uncertainty leading to difficulties in to interpret and learn from data<br>▪ Unclear if ML can be applied<br>▪ Organisational barrier to move personnel onshore |

# 3.4 TTA4 – Production, processing and transport




www.norskpetroleum.no

# Hypothesis related to Production, processing and logistics

## Hypothesis

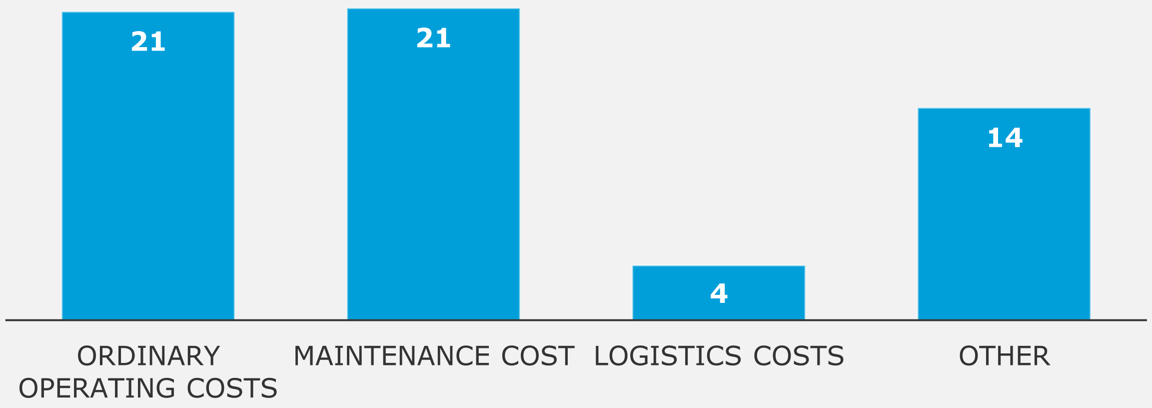
1. Maintenance and inspection can be optimized, giving
   - Cost savings and
   - Increased production and
   - Avoidance of costly repairs/trips

   via CBM (Condition based maintenance) and predictive maintenance enhanced by Machine Learning.
2. Digital Twins (process based) can be an aid in improving/maximizing production.
   1. On-line decision tool
   2. Autonomous operation
   3. Improving Energy efficiency
3. These technologies are enablers for Remote operation.

## Facts

- Total operating cost for NCS is 60 bNOK/year
- Where operation and maintenance is split equally.
- Logistics cost is ca. 4 bNOK/year

**Total Operations Costs (excluding tariffs & pre-ops)**
Average 2016..2019

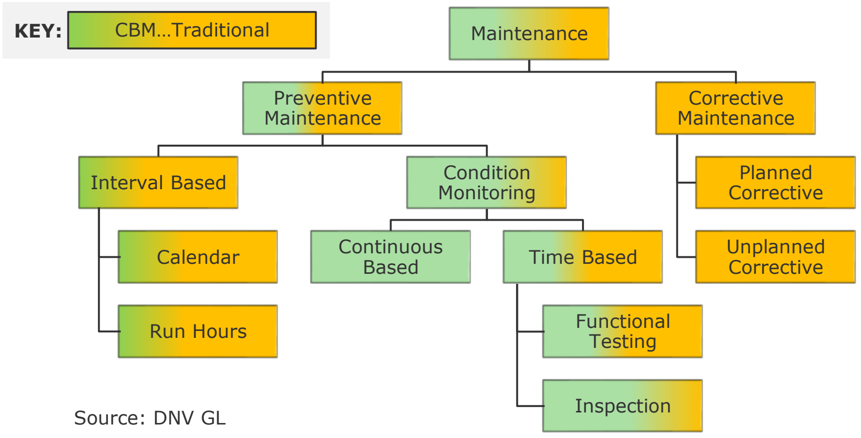



Ref.; NPD, 2020. Numbers in bNOK.

# Potential related to Condition Based Maintenance (CBM) and Predictive maintenance

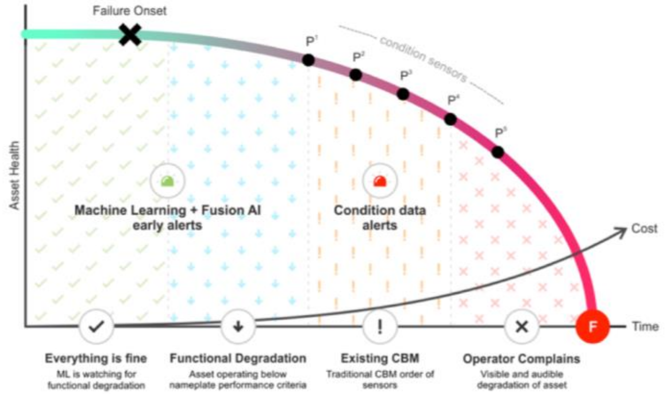
- **Status:** CBM is commonly used in NCS/O&G. Ca. 30% of maintenance activities is considered to be CBM based, such as inspections, testing, on/off-line monitoring (see figure).
- **Corrective maintenance:** About 50% of maintenance work (#of WO or hours or cost) is corrective, i.e. maintenance work after a reported failure.
  - Efficient techniques for Anomaly detection and RCFA (Root Cause Failure Analysis) will make the repair work more efficient. As well as learning from events to avoid repeated failures.
- **CBM:** Basic principle for CBM is to identify degradation as function of time (P-F curve), give early detection, and take remedial actions – planning and process changes – to avoid plant shutdown and costly repair (see figure).
- **Predictive maintenance**: Advanced models for prediction, either based on measured data, physical models or combination. Commonly used for structural integrity, topside corrosion, pipeline/riser integrity – named Risk Based Inspection (RBI).
- **Anomaly detection**: Interpretation of monitoring data to determine root cause of failure for efficient repair/recertification after an event.
- **Potential**: Develop & implement CBM, anomaly detection and Predictive maintenance techniques further by utilizing sensors, models and statistical data in combination. *ML will enhance this process.*
  - Goal should be to move from ca. 30% to 60% CBM.
  - But; CBM will not "heal" the equipment – repair needs to be done

**Current level of CBM technology implementation**




Source: DNV GL

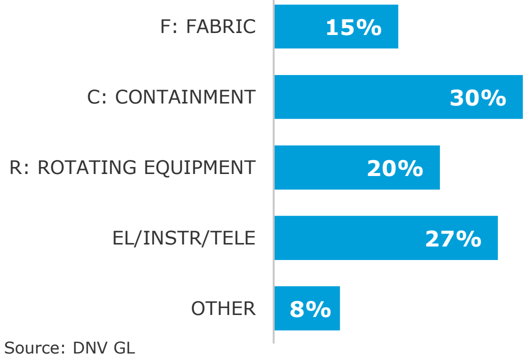
**P-F Curve 4.0** The role of Machine Learning




www.quartic.ai/smart-industries/predictive-maintenance

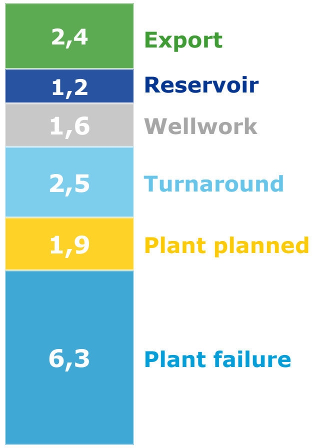
# TTA4.1: Condition Monitoring of Process plant technical condition

**Typical Maintenance Cost Distribution**




Source: DNV GL

**Average production Loss by Category from 2015 – 2017**
Actual production vs MPP (Max Production Potential)




Source: McKinsey

## Challenge

Maintenance cost represent 30% of total operating cost in NCS.

- More than 50% of the maintenance work is trigged by unforeseen failures of the asset (Corrective maintenance).
- More than 50% of the preventive maintenance work is time based and not condition based.

The industry and "maintenance professionals" are convinced that CBM based maintenance will benefit the industry enlarge.

## Opportunity

Condition based maintenance strategies will:

Reduce maintenance cost (OPEX) by:

- Improve maintenance planning.
- Increase maintenance intervals as work is called for based on actual condition of the equipment.
- Prevent breakdown of equipment .

Increased uptime as failures/trips can be avoided.

## Benefit for the O&G industry

- Maintenance cost represent about 20 BNOK/year for NCS (NPD 2020).
- Overall improvement opportunity based on applying CBM is from 5 to 30% based on industry experience, representing 1 to 6 BNOK/year savings due to early detection and extended PM intervals.
- The ML opportunities differs between system groups, where EL, R and C (se fig) got the highest potential.
- Uptime: average plant unavailability due to plant failure is ca. 5-6% (production loss). About 1/3 of the losses can be avoided, so that the unavailability drops from 5-6% down to 3-5%.

### CBM and ML:

Machine Learning is part of some of the CBM solutions today. ML must be combined with physical models, and statistical data (industrial sharing) to give full benefit. About 25% of the potential CBM benefit is related to use of ML.

### Barriers for ML:

- Few failure cases for ML to learn.
- Anomaly detection is a good candidate for ML, but "automatic" WO generation and task proposal is not mature.
- Lack of systematic data structure hindering comparison between assets.

### Enablers:

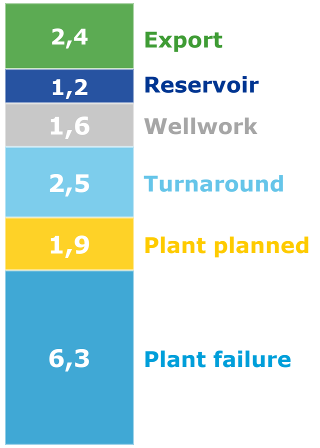
- Data infrastructure
- Industry wide sharing of information like OREDA, RNNP should be strengthened – i.e. learn from the industry not only from own plant (in particular for the smaller operators).
- Concepts exists today via both traditional enterprises and new companies.

### Risks:

- Wrong prediction - too conservative or too aggressive) leading to either unnecessary shutdowns or unplanned shutdowns.

# TTA4.2: Production optimisation

**Average production Loss by Category from 2015 – 2017**
Actual production vs MPP (Max Production Potential)




Source: McKinsey

| | |
|---|---|
| **Challenge** | The plant control is done by a combination of manual procedure and cybernetic based process control – balancing max production and safety for plant and human. The systems are complex, and due to safety, the procedures involves conservative settings.<br>Non-optimal production will appear frequent due to process events, slugs, well start/stop, trips, etc.. |
| **Opportunity** | **a) Adaptive process control*** can enhance the plant performance. This is standard technology from the SAS vendors, and have been on the market for many years. Also proprietary (operator made) solutions exists.<br>**b) Process Digital twins** are fieldwide (or part process) simulators running in parallel to plant – "guiding & advising" the operators. The models can cover the whole field, or a small part of the plant (e.g. virtual flow meetings, energy usage, slug handling, etc.). These models can be semi static (linearized & response surface based) or fully dynamic.<br>* Defined as a type of ML |
| **Benefit for the O&G industry** | ▪ Adaptive process control: Cases have shown 2 to 5% improvement in total production volumes.<br>▪ DTw-Energy savings: promising results for better energy performance of plants by avoiding "controllable" losses.<br>▪ DTw-Control room assistance to handle events and alarms: reported 3-8% production improvement via avoiding trips.<br>▪ Well control (choke and valve settings): significant volumes can be achieved, primary manual process today. |

**DTw (Digital Twin) and ML:**

DTw should primary be based on physical models; either directly or simplified. ML, AI, knowledge based models can enhance performance.

**Barriers:**

- ML perceived as black-box giving lack of user acceptance.
- Models too heavy to run faster than real time – "smarter" solutions needed.
- Cost of development for large scale simulators vs business potential.

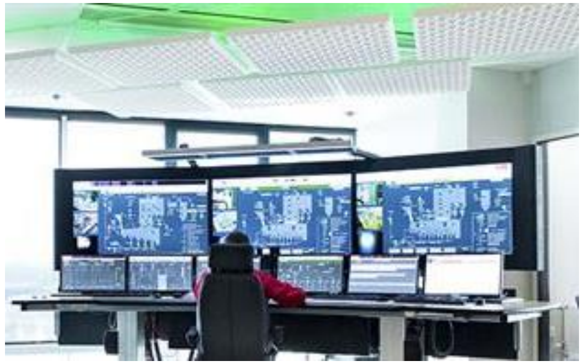
**Enablers:**

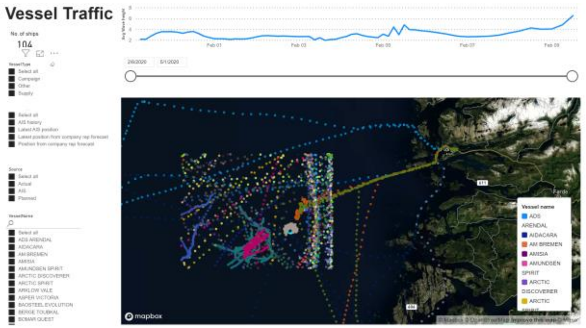
- Control systems enabling adaptive control
- Computer power and networks capacity
- Current process simulators exists for most fields and is a good starting point for real time DTw development

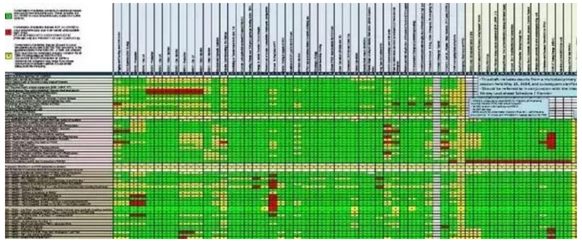
**Risks:**

- If all the processes are automatic, the operators will get less situational awareness as they don't train on difficult situations. But if good implementation is done, the operator can see the bigger picture and keep control on other thing than the machine can.

# TTA4.4: Logistics and integrated planning





### Challenge

Transport cost and energy usage is significant.  Collaborative efforts has been tested but it is believed that the potential is not exploited.

SIMPOS and Waiting time is a challenge related to new development/installation and modifications.

Optimal operational based transport to/from installations can be optimized.

### Opportunity

**Transport/installation:** ML can be used to optimise usage of supply vessels depending on sailing time, weather data, sailing speed VS fuel consumption and time spent at installation.

**Spare:** ML used for identification of correct spares (and alternative spares) from vendor data.

Logistics include all offshore activities like production, maintenance, drilling, modifications, installation work, logistic.  Constraints are PoB, transport capacity, cost, etc..

Share data and services related to transport for:

- SIMOPS solutions resulting in Reduction of waiting time and improved safety
- Collective solutions between licences
- Sharing of transport resources

Logistic cost: ca; 4 bNOK/year

### Benefit for the O&G industry

- Reduced logistic cost
- Reduced waiting time
- Reduced emissions
- Potential not quantified at this stage.

### DTw (Digital Twin) and ML:

Logistics models in combination with ML may be a solution.

### Barriers:

- The licences are autonomous with its own budgets
- Priority and planning is complex if several users are to be served

### Enablers:

- Connectivity between ships, operations centres and base is well developed and in use

### Risks:

- No significant risks

# Production optimization/ML; Cases:

| Case | WHO | Effect | Development stage |
|---|---|---|---|
| **Process Adaptive control** – MPP enhancement via more stable process running closer to max capacity. | Equinor, Lundin ABB & Honeywell | 2-5% production increase | Industrialized and in use |
| **Virtual flow** meters for well control | AkerBP, Cognite, TFMC | Reservoir management related to sub-sea tieback. Optimisation of well testing, prioritize of wells production. | Pilot |
| **Energy monitoring**, and energy loss assessment. On-line to control room for immediate action. | Lundin | Reduction of energy usage by 15-20% for key energy consumers. | Pilot |
| **Flow management; slug** handling – prediction and control of how to avoid process upsets | Lundin, Aker BP, Cognite | Stable high production with less disturbances. | Industrialized and in use |
| **Process Digital Twin:** Failure/trip avoidance and alarm handling via process DTw | Kairos for Equinor, Repsol, Total | 3-8% production enhancement | First application |
| **Water contamination detection** | AkerBP & Cognite | | Pilot |
| **CBM Digital Twin:** Large turbine monitoring by means of digital twins applying ML/Adaptive learning (Smart Signal by Baker Hughes) | ConocoPhillips | Early detection of anomalies. | Industrialized, and used for 10+ years globally. |



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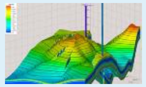
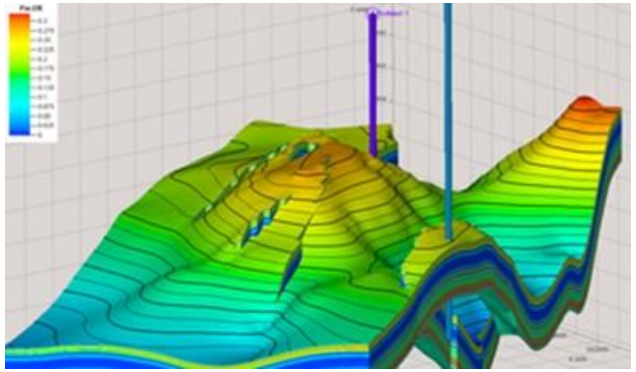
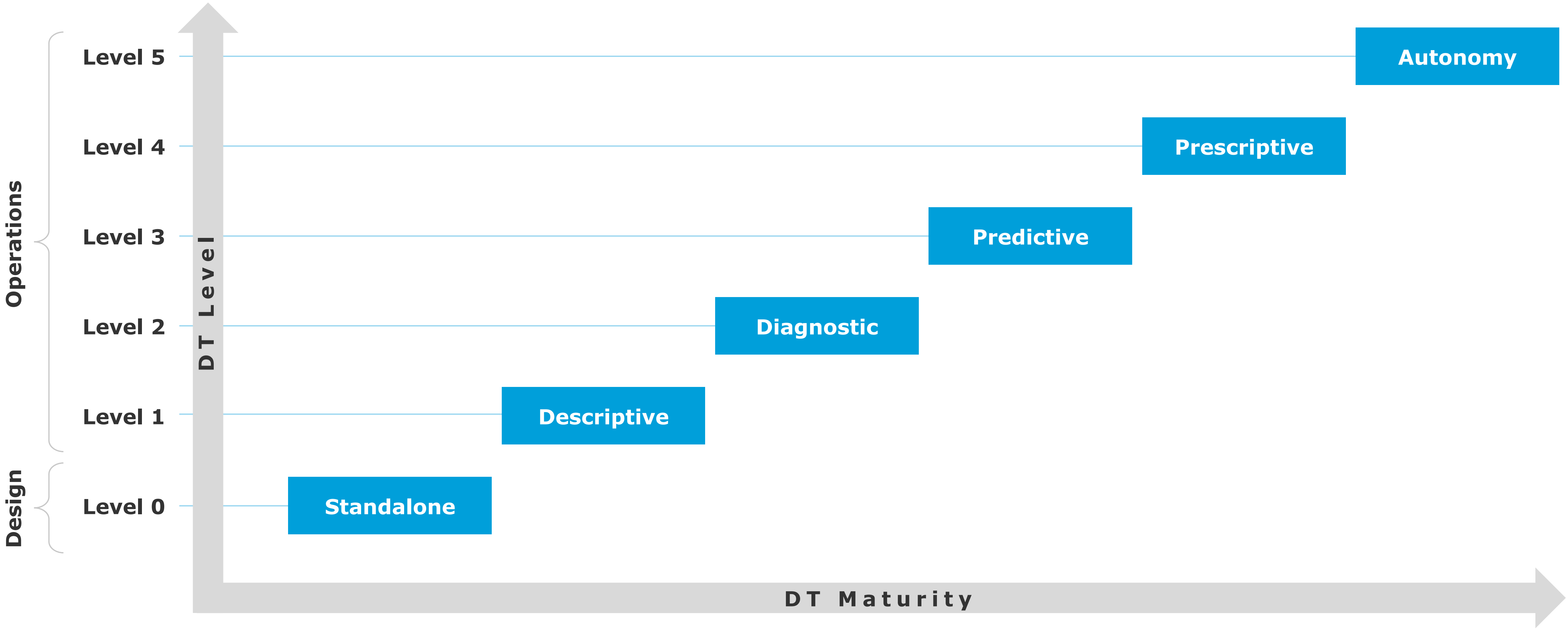
# What are Digital Twins?

***Digital Twin*** **is a virtual representation of a system or physical asset, that makes system information available or predicts performance through integrated models and data, with the purpose of providing decision support.**

| # | Category | Type | Usage | ML enabled |
|---|---|---|---|---|
| A  | Design and manufacturing twins | ▪ Discipline oriented: (process, safety & environment, structural/environmental impact, flow assurance,… | ▪ Detailed Design, engineering tools, tailored to individual plants.<br>▪ A subset, e.g. 3D models used during operation. | Limited |
| B  | Operation Performance based – on-line | ▪ Field wide or sub-models for dedicated purpose<br>▪ Standalone solutions<br>▪ Integrated with control system | ▪ Decision support; operator assistance<br>▪ Anomaly detection<br>▪ Energy management<br>▪ Process optimising – stability, start/stop, process control. | AI, ML, and data analytics applied |
| C  | Operation Performance based – off-line | Engineering tools to analyse performance, debottleneck. Similar to A) | Engineering analysis of performance, engineering changes based on operational data<br>Reservoir management. | Limited |
| D  | Operation - Condition based (CBM) & predictive maintenance | On-line measurement of equipment degradation and prediction of time to failure | ▪ Alarm in control room<br>▪ Anomaly detection<br>▪ Maintenance planning | Common to use AI and ML |
| E  | Reservoir models | Reservoir models including 4D seismic can be viewed as a digital twin solution. | ▪ Monotiling of reservoir drainage<br>▪ Injection planning<br>▪ Estimation of water breakthrough | Limited |



# Evolutionary stages / Ambitions of digital twins




…see definitions next page

# Digital Twin – different levels of maturity

**Level 0 - Standalone**: The DT will typically consist of multiple models with the purpose of supporting decision making during the different engineering and design phases. This includes graphical models, bill of materials, multidomain modelling to support simulations and virtual tests for design verification, manufacturing and operation prior to putting the asset into operation. Several models may be combined into a system of systems in order to simulate the interaction between these systems as well as external interfaces such as the environment or other systems. This level provides a standalone description of the system, disconnected from the real environment.

**Level 1 - Descriptive**: The collection of models, engineering data and information generated in level 0, are aggregated with live sensor data from the real system to be contextualized and structured including all relevant links from the real world [31]. The DT can describe the real system, providing status, alarms and events, based on the integrated live data at a basic level. Offline operations and maintenance data up to date, shall be synchronized as soon as information is available. At this level the DT instances shall be able to be interrogated and provide information about its current and past histories. Dashboards, 3D models, interactive drawings integrated with live data, among others may be part of the visualization tools at this level. Basic monitoring and fault detection to support descriptive capabilities may be available, based on limit checking, trend checking and pre-defined acceptance criteria checking. The contextualized and structured information from disparate data sources, together with the visualization tools, may facilitate monitoring tasks to operators and technical experts.

**Level 2 - Diagnostic***:* This level contains all contextualized data and information included in level 0 and 1. In addition the DT can learn, adapt and evolve continuously with Real Time data beyond supporting snapshots from the visualization system or historical information. At this level, dynamic models with adaptive capabilities shall be available, and the construction of models to support health indexes and condition indicators are important [11]. Diagnostic information shall be incorporated within the visualization tools. Therefore, capabilities available at this level are able to support operators and technical experts on equipment and process condition monitoring, fault finding and troubleshooting tasks.

**Level 3 - Predictive**: This level contains all contextualized data, information, models and capabilities included in level 0, 1 and 2. In addition, the DT contains aging, degradation, short- and long-term evolution models to predict future states based on current status and histories from multiple instances. This level shall have the ability to predict process and equipment performance as well as remaining useful life. Health indexes and condition indicators are further enriched to support prognostic capabilities. Prognostic information shall also be available within the visualization tools, suitable for different prediction horizons within the remaining lifetime. DT capabilities at this level are able to support operators and technical experts with process and equipment condition-based assessment and predictive maintenance tasks. Depending on the application, this level could also include prescriptive capabilities. Alternatively, they can be fully developed in level 4.

**Level 4 - Prescriptive**: This level contains all contextualized data, information, models and capabilities included in level 0, 1, 2 and 3. In addition the DT is equipped with prescriptive analytics to support recommended actions based on the available predictions, including the implications of each decision option [37] and how to optimize the future actions without compromising other priorities. This level may support multiple scenario simulations, improvements and optimizations within asset operations, equipment maintenance, repairs, risk mitigation as well as business decision making. These capabilities may also support remote operations of minimum manned or unmanned facilities.

**Level 5 - Autonomous***:* This level contains all contextualized data, information, models and capabilities included in level 0, 1, 2, 3 and 4. In addition the DT can replace operators or technical experts directly by closing the loops to make decisions and execute control actions or tasks that can be completely automated.



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# 4 Overview of interviews and workshops conducted

# Overview of interviews and workshops conducted

## Workshops:

- TTA 1 – 28th April
- TTA 2 – 21st April
- TTA 3 – 23rd April
- TTA 4 – 29th April

## Interviews

Period May 4th – June 11th

## Interviewees:

**Aker BP**, Prashant Kumar Soni, Kjell Kristian Ask, Christian Borsheim Jacobsen

**Arundo**, Tor Jakob Ramsøy, Martin Lundqvist

**Cognite**: Jon M Lervik, Petter Jacob Jacobsen, Carlo Caso

**COP**, Jonas Rydland, Mayo Kiritharan, Mike Herbert

**Dataiku**, Florian Douetteau

**Digital Norway**, Helge Dahl-Jørgensen, Trond Moengen, Eirik Andreassen

**DNV GL**, Erik Østby, Pål Rylandsholm

**Earth Science Analytics**, Eirik Larsen

**eDrilling**, Anwesha Mal

**Equinor**, John-Morten Godhavn, Bernt Edvard Tysseland, Merete Lunde, Florian Schuchert, Christian Collin-Hansen, Jens Grimsgaard, Harald Laastad, Carl Fredrik Eek-Jensen, Fakhri Landosi

**Halliburton**, Rob Berendsen, Chafaa Badis, Margareth Gibbons

**Kongsberg Digital**, Shane McArdle, Eivind Rosen Eide

**Lundin**, Kim Jørgensen, Stein Erik Hilmersen, Jan Erik Lie, Erik Tveit

**Microsoft**, Christian Tryti

**NPD**, Arne Holhjem

**NTNU**, Egil Tjåland, Asgeir Sørensen, Alexey Pavlov, Lars Imsland, Kenneth Duffaut, Jørn Vatn, Andrei Lobov

**Petoro**, Erik Søndenå, Roy Russå

**Sekal**, Egil Stranden, Asbjørn Sola

**Shell,** Rolf Einar Sæter

**Schlumberger**, Trygve Randen

**Solution Seeker**, Vidar Gunnerud

**Stanford**, Hamdi Tchelepi, Biondo Biondi, Margot Gerritsen

**TechnipFMC,** Dag Ljungquist

**UiO**, David Cameron

**UiT**, Torbjørn Eltoft

**4Subsea**, Christoffer Nilsen-Aas

# 5 Reference material

# Main sources of reference material

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- WE Forum digital transformation, Oil&Gas specific report (WE Forum, 2017).
- Energi21, Digitalisering av energisektoren Anbefalinger om forskning og innovasjon (2020)
- NPD, Resource Report for Discoveries and Fields 2019
- Oil & Gas for the 21st century, Strategy Document, OG21
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- BRU21 Better Resource Utlization in the 21st century
- Annual report 2019, BRU21, NTNU Research and Innovation in Digital and Automation Solutions for the Oil and Gas Industry
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- Digital Transformation Initiative Oil and Gas Industry, World Economic Forum (2017)
- De nasjonale forskningsetiske kommiteene, Forskningsetisk betenkning om kunstig intelligens (2019)
- Rapport fra ekspertgruppen for datadeling i næringslivet (2020)
- Teknologirådet, Kunstig Intelligens, Muligheter, utfordringer og en plan for Norge (2018)
- Datatilsynet, Kunstig intelligens og personvern (2018)
- Forskningsrådet, Effekter av Forskningsrådets målrettede aktiviteter innen petroleum (2020)

# 6 Terminology

# Terminology

**agent (in reinforcement learning)** : a part of learning algorithm which makes observations and take actions within an environment, and in return it receives rewards. Its objective is to learn to act in a way that will maximize its expected long-term rewards (Geron, 2017). Source: Geron, Aurelion, 2017. Hands-on machine learning with Scikit-Learn & Tensorflow. O'Reilly, USA.

**algorithm*** : generic term for a set of instructions, typically implemented as computer code, which perform a specific task. The code which takes training data and produces a model is itself an algorithm, but in this RP algorithm is used a synonym for model.

**application*** : piece of software intended to be used for a specific, defined, purpose. See also data-driven application.

**data-driven application*** : application which includes at least one data-driven model. The parameters and configuration of a data-driven model are automatically determined (or learned) from data using a suitable algorithm.

**data-driven model*** : model which is made by applying a suitable training algorithm to a set of data.

**first-principle model** : a model which is developed based on nature/physical laws, such as mass balance, energy balance, heat transfer relations, and so on; rather than primarily on data.

**machine learning*** : subfield of AI concerned with performing a specific task without using explicit instructions.

**model*** : computer-based representation of some process and/or entity, which is typically used to make predictions and/or other useful transformations of input data.

* definition taken from DNVGL-RP-0510 Framework for assurance of data-driven algorithms and models

# 7 Background data and calculations for potential ML estimates

# Background data and calculations for potential ML estimates (1 out of 2)

| Application areas (TTA): | | Key opportunities | Unadjusted (ML) Potential | PoS | Data basis | Potential reduction |
|---|---|---|---|---|---|---|
| 1 | Energy efficiency and environment | Process digital twin energy savings: promising results for better energy performance of plants by avoiding “controllable” losses | ÷10% GHG reduction<br><br>10% figure from ML applied business case from interviews | ~70% | 14.2 Mega tonn CO2/yr gassturbin; 11.6 (14.2 million ton)<br>1 Mt = 1000.000.000 kg. | 0.9 Mt CO2/yr |
| 2 | Exploration and increased recovery | Better reservoir management<br><br>ML is unbiased, thus offer an opportunity for more objective reservoir modeling.<br><br>Faster model update (50%). | Reduced time and manning in operations phase estimated to 200 MNOK per year based on feedback from interviews. | 50% | • 50% PoS | 100 MNOK per year reduced OPEX considering 50% PoS |
| 2 | Exploration and increased recovery | About 4 months accelerated production due too faster seismic processing and interpretation.<br><br>Better understanding of prospects and better basis for decision to drill. | About 20% reduction in required resources per prospect<br><br>Better drilling decisions using ML in exploration leading to one additional discovery per year. | 90% | • Average 8 required resources per prospect<br>• 2 MNOK per resource<br>• 20 prospects<br><br>• Average size of 5 million SM3 o.e. (conservative estimate based on “OD ressursrapport 2018”) | • 60 MNOK reduced appraisal cost per year<br><br>• 5 million SM3 o.e. additional discovery per year |
| 2 | Seismic processing and interpretation | Reduced lead time for seismic processing and Interpretation | 20% reduced time from procurement of seismic to decision to drill | 90% | • 20% reduced time from procurement of seismic to decision to drill based on feedback from interviews indicating at least a factor 10 reduction in time and effort for seismic processing and interpretation<br>• On average about 20 months (ref. NPD Arbeidsprogram / vilkår) from procurement of seismic to decision to drill<br>• 20% of 20 months equals 4 months accelerated production<br>• Assuming 5 new discoveries per year with an average size of 5 million SM3 o.e. (conservative estimate based on “OD ressursrapport 2018”) and that all these discoveries will be developed (5 per year). This corresponds to a yearly accelerated production of 1 mill SM3 o.e. the first year. The effect will be diminished and cancelled out over time when the first developments fall off plateau. The value of the accelerated production is small since the entire project (including the cost) is accelerated. | |

# Background data and calculations for potential ML estimates (2 out of 2)

| Application areas (TTA): | | Key opportunities | Unadjusted (ML) Potential | PoS | Data basis | Potential reduction |
|---|---|---|---|---|---|---|
| 3 | Drilling, completions and intervention | ML applied in autonomous drilling and parameter optimization to increase efficiency. | 20% reduction of well delivery time<br>20% reduction in sidetracks<br>Sidetracks required in 20% of wells<br><br>20% figure from ML applied business cases from interviews | ~80% | Drilling cost=rig hire= 300 k$/day; 70 days/well, 130 wells/year,<br>8 NOK/USD | Tot saving: ca. 3-4 bNOK/year<br><br>GHG reduction of 0.06 Mega ton, representing 6% of drilling activities release (1.06 Mega ton) |
| 4 | CBM, Predictive maintenance | ▪ Reduced unplanned expensive repairs<br>▪ More optimized and streamlined PM program<br>▪ More condition based maintenance | OPEX: 15% reduction - Less costly failures<br>- Less frequent inspection/testing/maintenance based on DNV GL experience | 60% | 21 bNOK/year includes<br>▪ Maintenance excluding wells<br>▪ Well maintenance<br>▪ Subseea operations and maintenance | 2 bill NOK/year |
| 4 | CBM, Predictive maintenance | ML applied for<br>▪ Early warning avoiding prolonged shutdown,<br>▪ Extending intervals for PM intervals requiring shutdown | 1,5% accelerated production 1/3 reduction in unplanned losses<br>- 25% reduced losses in planned losses<br><br>based on DNV GL experience | 60% | Total production 214 mill Sm3 o.e (2019)<br>6% unplanned failures<br>2% loss planned maintenance | 2 mill Sm3 o.e. |
| 4 | Production optimization | ▪ ML applied for production optimization | Assumed 5% additional accelerated production potential to Maximum Production Potential through ML applied in well optimization and adaptive control | 60% | Total production 214 mill Sm3 o.e (2019) | 6 mill Sm3 o.e. |

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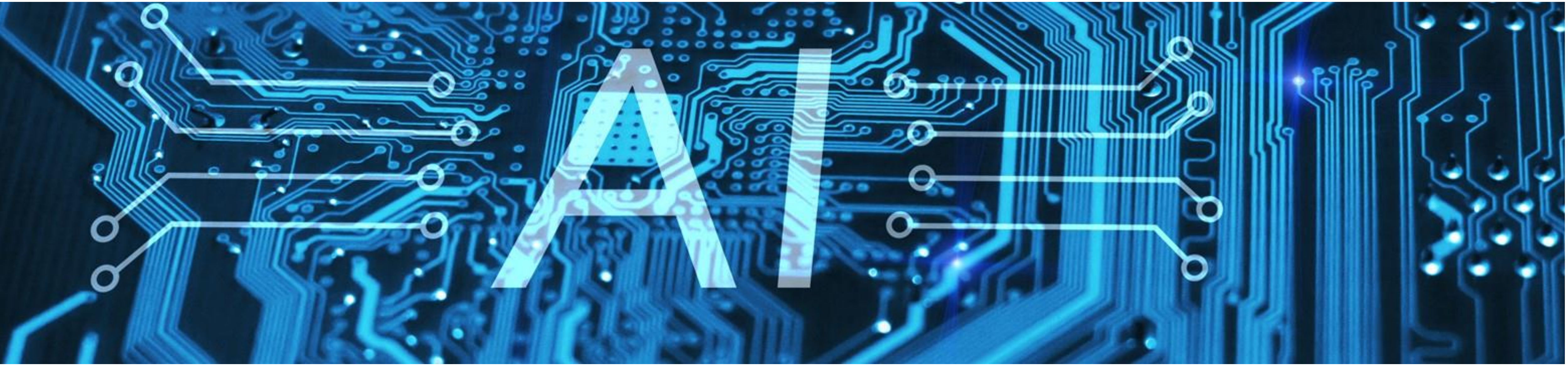


**Contacts: Hans Petter Ellingsen & Sture Angelsen**

Hans.petter.Ellingsen@dnvgl.com

Sture.Angelsen@dnvgl.com

+47 47675638; +47 4161 2741

dnvgl.com