FEASIBILITY STUDY ON ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN NUCLEAR APPLICATIONS

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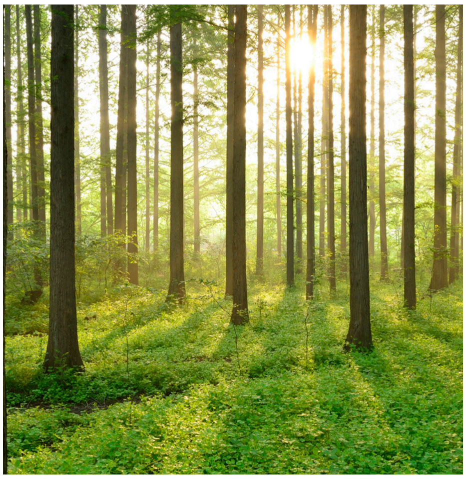

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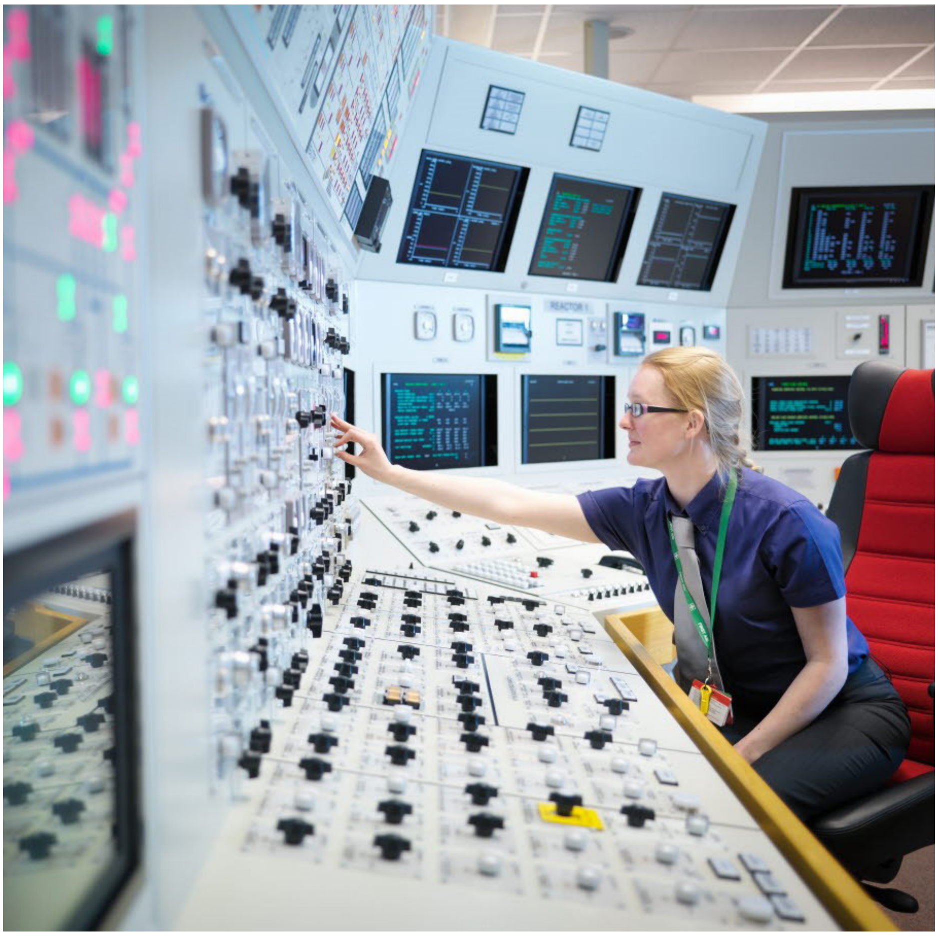

Energiforsk

Feasibility Study on Artificial Intelligence Technologies in Nuclear Applications

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Foreword

The Energiforsk program *Digitalization in nuclear applications* aims to facilitate and enable digitalization in the Nordic nuclear power plants. Artificial intelligence (AI) has a large potential within many industrial processes and has today quite low utilization within the nuclear industry. AI is also a 'buzz' word where it easy to get lost, therefore guidance is needed to choose the appropriate tool to implement.

This study aims to gather knowledge on artificial intelligence technologies (AI) suitable for the Nordic nuclear power plants in general. Two themes have been identified and are in focus:

- Digitization of documentation
- Assisting operation-, technical- and maintenance staff in taking informed decisions regarding operation, plant development and maintenance.

With about 40 years of operations and a lot of data from measurements, inspections and maintenance, digital tools should have the potential to facilitate the continued safe operation of our nuclear power plants,

The survey was carried out by Ulf Nygren and a team at AFRY. The *Digitalization in Nuclear Applications program* is a part of the Energiforsk nuclear portfolio, financed by Vattenfall, Uniper, Fortum, TVO, Skellefteå Kraft and Karlstads Energi.

Abstract

This report gives an overview and conclusions on the challenges and opportunities that nuclear utilities will face, in finding and using suitable artificial intelligence (AI) applications. The basis for the report is a series of interviews with nuclear utilities, institutes, and suppliers, trying to find the areas of interest to introduce AI for the nuclear industry.

The focus of the study has been to collect opinions and ideas from different nuclear utilities, institutes and suppliers with regard to challenges and opportunities that makes it possible to introduce AI for nuclear applications. This has been done through a series of interviews with different stakeholders.

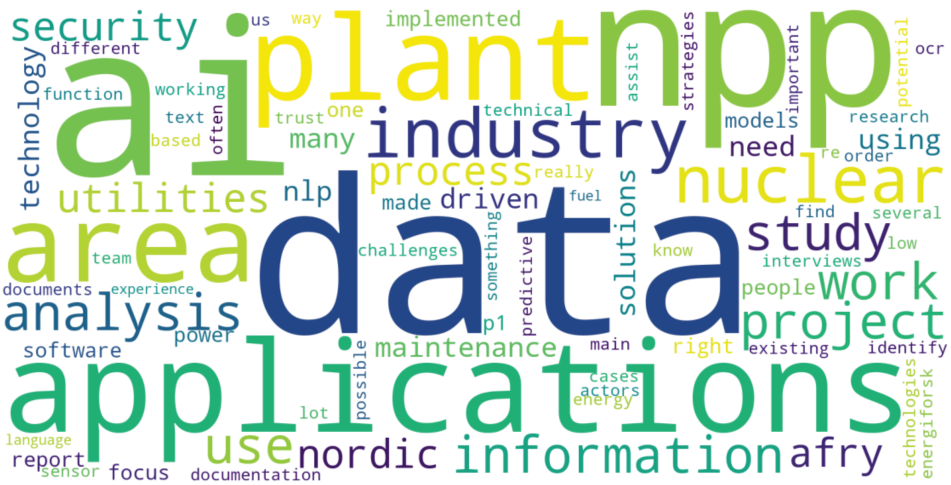
The main conclusion is that there is an underlying scepticism against software in nuclear, and AI applications are no exception - rather the opposite. Still, there is a considerable amount of possible applications mentioned by different parties. Hence, this report presents many of the ideas brought up during the interviews, but also conclusions from the compilation of the interviews.

Sammanfattning

Rapporten ger en översikt och slutsatser kring de utmaningar och möjligheter som kärnkraften står inför när det gäller att hitta relevanta användningsområden för artificiell intelligens (AI). Grunden för denna rapport har varit en serie genomförda intervjuer av aktörer inom kärnkraftsindustrin, -institut och -leverantörer, i syfte att få fram de mest intressanta områdena för att introducera AI inom kärnkraften.

Huvudfokus för studien har varit att samla åsikter och idéer från kärnkraftsindustrin, -institut och -leverantörer beträffande utmaningar och möjligheter med att introducera AI-applikationer inom kärnkraften. Detta har gjorts genom en serie genomförda intervjuer med ett antal olika intressenter.

Huvudslutsatsen är att det finns en underliggande skepsis till programvara inom kärnkraftsindustrin. AI-applikationer är inget undantag – snarare motsatsen. Trots detta finns det en ansenlig mängd potentiella applikationer som har föreslagits av olika parter. Följaktligen presenterar denna rapport ett flertal idéer som har tagits upp under intervjuerna, men också slutsatser från sammanställningarna av intervjuerna.



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1 About the project

The nuclear industry is heavily regulated, leading to massive amounts of documents throughout a plant's lifetime, and additionally, while in production, several types of data are used for monitoring the plant. AI is a set of technologies that automatically can turn these vast amounts of data into important information.

Safety and security are critical aspects and thus cyber security, e.g. on-premise data management and local IT governance are key.

According to Energiforsk, the Nordic Nuclear Power Plants (NPPs) have a limited level of experience, utilization, and implementation of AI for assisting the work within the nuclear power plants. Large international NPPs have come quite far in implementing solutions, but in the Nordics the progress is limited.

The application areas that the study will focus on are the digitization of documents, and how the operation-, technical- and maintenance staff can be assisted in taking informed decisions regarding the operation, plant development, and maintenance.

Thus, utilizing AI combined with Optical Character Recognition (OCR) and Natural Language Processing (NLP) technologies to digitize, analyze and manage information efficiently, (also combined with cyber security solutions) has the potential to be very beneficial for the Nordic NPPs.

The main purpose of the project is to map out and document how other NPPs and actors within e.g. energy industry have adopted AI and to advise on how to apply such findings and experiences to the Nordic NPPs and some of their identified needs.

The purpose of this study is to gather knowledge on AI technologies suitable for Nordic nuclear power plants to conduct a feasibility study on artificial intelligence technologies in nuclear applications.

The goal is to have a wide area of focus while narrowing down on identifying “low hanging fruits” from a nuclear perspective.

The main focus areas will be for digitizing documentation and assisting operation-, technical- and maintenance staff in taking informed decisions.

2 Abbreviations, Terminology and Acronyms

AGI	Artificial General Intelligence
AI	Artificial Intelligence
ANI	Artificial Narrow Intelligence
AR	Augmented Reality
BERT	Bidirectional Encoder Representations from Transformers, one example of a state-of-the-art NLP model
CAP	A Corrective Action Programme, is the system for how a utility should find and fix problems at the plant. An expensive and a time-consuming process, legislated in the US
Corpus	Body of text, text dataset. Commonly used in NLP
CV	Computer Vision
CWNC	Curtis-Wright Nuclear Canada
DAPT	Domain-Adaptive Pre-Training
DBA	Design-Based Accidents
Digitalization	Converting business processes from analog/offline systems do digital technologies
Digitization	Converting something to a digital format, e.g. scanning a document and making machine-readable
EA	Expert Advisor
EDA	Exploratory Data Analysis, refers to the process of analyzing data sets, by performing investigations on data to discover patterns, spot anomalies, test hypotheses, and check assumptions, with statistical and graphical representations.
EPRI	Electric Power Research Institute
FAC	Flow Accelerated Corrosion
HVAC	Heating, Ventilation, and Air Conditioning systems
IAEA	International Atomic Energy Agency
iFTF	AI-based Fuel Transport Function
IoT	Internet of Things
ML	Machine Learning
NDE	Non-destructive evaluation – Testing and analysis technique commonly used in many industries
NGO	Non-Governmental Organisation
NLP	Natural Language Processing
NPP	Nuclear Power Plant
NRC	Nuclear Regulatory Commission
OCR	Optical Character Recognition
OLAP	Online Analytic Processing
OLTP	Online Transaction Processing
QA	Quality Assurance
ROP	Reactor Operators
RUL	Remaining Useful Life
SAR	Safety Analysis Report

SKB	Swedish Nuclear Fuel and Waste Management Co
SMR	Small Modular Reactor
Text mining	The process of transforming unstructured text into structured data for easy analysis
TOP	Turbine Operators
Utility	A specific nuclear power plant, e.g. Ringhals, Forsmark, not the owner such as Uniper or Vattenfall

3 Introduction

3.1 BACKGROUND

3.1.1 General Position of AI in European Business

The knowledge and awareness of the possibilities with AI are constantly increasing all over the IT field. A recent survey by The Economist, Intelligence Unit, in May and June 2021, where 1002 IT decision-makers around Europe were asked about their near future IT investment plans, showed that Machine Learning (ML) and AI have the highest priority of all areas. Even higher priority than cloud computing and automation, see Figure 1.

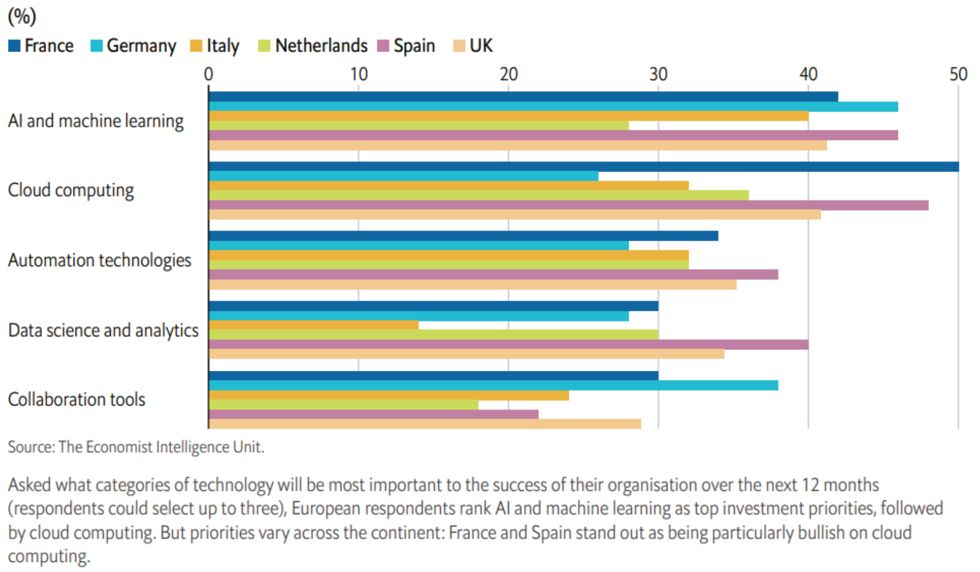

Figure 1: AI - European business leaders' investment priority list

The investment in AI solutions for the nuclear industry will not be an exception to this trend. This report will highlight some of the many possibilities of AI in the nuclear industry, and some of the challenges.

3.1.2 Understanding AI Development in Nordic NPP Industry

A study worth mentioning, is ”Myndighetsstöd: Competency based assessments of Nuclear Power Plant controlroom operators” Castor, M. and Borgvall, J. (Geistt AB) [1], where the purpose is to get an orientation of the different definitions and terminology used in the AI domain as well as to map out a current understanding for how the development and plans look like within the Swedish NPP industry.

3.2 A BRIEF THEORY OF AI

It was not until recently that the hype and interest in AI exploded. The main reason for this is the technical development that has made it possible with regards to increased opportunities to compute the large amount of data needed to feed into an AI network for it to be able to accomplish tasks, such as classifying images as well as recognizing and classifying text. In addition to this, computational power and memory are a necessity to process huge amounts of data.

AI can be divided into two categories, artificial narrow intelligence (ANI) and artificial general intelligence (AGI), see Figure 2. These concepts are vastly different;

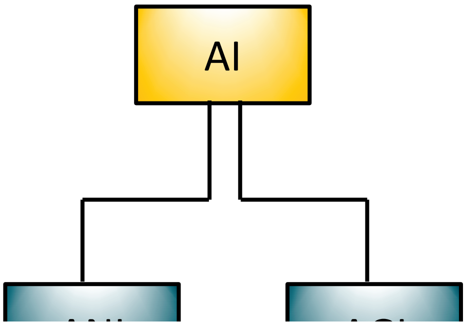

Figure 2: AI divided into two categories, ANI and AGI.

while ANI specializes in things such as image recognition, text analysis etcetera, AGI aims to emulate and even surpass humans, including human intelligence. AGI is what is generally referred to as AI in movies and popular myths since it renders itself well to a dramatic format. However, it is worth noting that while there has been little progress with regards to AGI, ANI on the other hand is used to great success and creates immense value [2].

3.2.1 Machine Learning

Machine learning (ML) is a subcategory of AI, and it is often what is meant when talking about AI. ML can be described as learning, reasoning, and acting based on data. A mathematical machine learning model is trained on data, to make decisions or predictions from patterns it has learned during training. In ML, it is quite arbitrary what the data represent; furthermore, general methods can be useful in a wide range of applications in different domains [3].

ML is often divided into supervised learning, unsupervised learning, and reinforcement learning. In the following sections, unsupervised and supervised learning are described as they are relevant for this study.

Supervised Learning

In supervised learning, as described by Lindholm et al. [3], the dataset contains input variables and output variables. The input variables, represented by an x vector, are called features and the output variable y, is called a label and is used to validate the result into a certain category. An example would be predicting which music group wrote a certain song based on different input features. The features x

could be duration, tempo, energy etcetera, where each feature is represented by a value in the x vector. These values could be extracted from a music program or an API. Furthermore, the label y would be a scalar value, where each value represents a band, thereby classifying the data. The dataset of songs can be denoted as $\tau\{\boldsymbol{x_i}, y_i\}_{i=1}^{n}$. By using the labeled data τ, a mathematical model or method is used, and it is adapted to the training data. This process is called training the model. The aim is for the model to find the relationship between the data and predict the output label based on new unseen data, often called test data.

The output of a supervised model can have two types, numerical or categorical. When the output is numerical, where the numerical value has a natural ordering, it is called a regression problem. When the output is categorical, as, in the above example, it is a classification problem.

Unsupervised Learning

Unsupervised learning is a method to analyze and cluster unlabeled data by using machine learning, and it is commonly used for exploratory data analysis. By utilizing unsupervised learning, hidden patterns and the grouping of data can be discovered. By clustering the unlabeled data, similarities and differences can be found, as well as categories and topics. This is commonly used by companies to understand relationships between products and the consumption habits of their customers [4].

3.2.2 Natural Language Processing

Natural language processing (NLP) is a subfield of AI, where AI is applied to text data. NLP can be used for chatbots, sentiment analysis, language translation, and much more. Since 2017, NLP has taken a giant leap due to the development of attention-based methods such as transformers like BERT, and bidirectional encoder representations from transformers. In late 2020, BERT was used in almost every google search query, helping users find relevant answers to their questions since BERT is excellent at capturing context [5]. Pre-trained transformers models, such as BERT, are very robust and accurate, as they are trained on massive amounts of data. For other languages than English, such as Swedish, the performance is not as good. Performance can also be an issue in specific domains, where the model has not been trained, such as the nuclear power plant domain. Furthermore, BERT is open-source and can be used for on-premises solutions, which is important for security in the nuclear power plant industry.

Tokenization

A computer cannot understand raw text in the format humans see it, therefore tokenization is needed. Tokenization is a method of turning text into numbers. By splitting the raw text into smaller chunks, e.g., the sentence, “The man gladly watched the neighbors’ dog.”, the tokenization: [“The”, “man”, “gladly”, “watched”, “the” “neighbor’s” “dog.”] is the result.

Transformers and BERT

Transformers were introduced by Google in the paper "Attention is all you need", by Vaswani et al. in 2017 [6]. The concept of attention and transformers architecture has since revolutionized the field of NLP. The transformers model uses a self-attention mechanism which gives the model the ability to focus its attention on the right place by understanding the context.

Bidirectional Encoder Representations from Transformers (BERT) is the first deeply bidirectional, unsupervised language representation method. It is pre-trained using only a plain text corpus such as Wikipedia, giving it the advantage of being able to train on a very large set of data, as there is no need for labeled data. BERT is contextual, and deeply bidirectional, compared to previous models. Contextual means that it gives a word its embedding (numerical values) depending on the context and not just the meaning of the word. For instance, when given a sentence with the words "bank account", BERT embeds the word "bank" based on context. Because of this, it gives a different embedding for "bank" than if the context was "sand bank". Accounting for semantic relationships is one of the great strengths of a transformers model [7].

Pre-training BERT takes a considerable amount of time and resources, however, due to BERT being a pre-trained model, the user of the model does not need to conduct the pre-training. By adding one additional output layer to BERT, it can be fine-tuned for various tasks, performing state-of-the-art results.

3.2.3 AI for Predictive Maintenance in Nuclear Power Plants

According to Energiforsk, the Swedish nuclear power plants have a limited level of experience in utilizing and implementing AI for assisting the work within the nuclear power plants [8]. Large international NPPs have come quite far in implementing AI solutions, but in the Nordics the progress is limited.

By implementing AI, large amounts of data can be analyzed in a smarter, cheaper, and more efficient way, thus helping the operators and decision-makers at the NPPs. Furthermore, utilizing AI technologies like NLP to digitize, analyze and manage information and text data can be very beneficial for NPPs. Once analyzed, it can be used to improve the work in operations and maintenance, e.g., by reducing time-consuming manual sorting tasks or finding trends in data.

3.3 SCOPE AND OBJECTIVES OF THE STUDY

The purpose of this study is to gather knowledge on AI technologies suitable for Nordic NPPs to conduct a feasibility study on AI technologies in nuclear applications.

The goal is to have a wide area of focus while narrowing down on identifying "low hanging fruits" from a nuclear perspective.

The main focus areas will be for digitizing documentation and assisting operation-, technical-and maintenance staff in taking informed decisions.

The following deliverables are the results of the project:

- A complete report describing the findings from the feasibility study using Energiforsk's standard template. The report is written in English and includes a summary in Swedish (file format: Word or PDF).
- A Power Point presentation to support the final presentation of the project results (file format PPT). A Power Point with an Executive Summary (3-5 slides that support a short presentation)(file format PPT).
- A face-to-face presentation of the results.

3.4 PROJECT SET-UP

For this project, AFRY has used a core team consisting of experienced personnel from the nuclear, digital applications and AI areas. In addition, interview methodology experts and subject matter experts have been at disposal as needed. This team has worked in collaboration with NPP representatives from the Energiforsk reference group.

The work has been divided into: technical overview, mapping of applications suitable for NPPs and next steps for Nordic NPPs. In addition to this, exploratory data analysis and algorithmic research have been added as a work area to dig down deeper into identified problem areas related to text data analysis.

3.4.1 Technical Overview

This encompasses introducing a technical overview of AI and present suitable technologies already utilised in the energy industry. Furthermore, it also includes gaining an understanding of AI plans and/or strategies in Nordic NPPs, as well as mapping relevant and similar initiatives in other industries.

3.4.2 Mapping of Applications Suitable for NPPs

This comprises investigating relevant AI applications for nuclear power plants with key areas of particular relevance being digitisation of documentation and assisting operation-, technical- and maintenance staff in taking informed decisions regarding the operation, plant development, and maintenance.

Furthermore, distilling information from interview subjects and mapping observations to AI techniques have been conducted by using interviews – the method for which can be found in Appendix A.

3.4.3 Next Steps for Nordic NPPs

This part of the study includes investigating future needs of AI technology considering different phases in the plant lifecycle. Moreover, a future vision and challenges to reach that vision have been identified, as well as outlining and accounting for main risks. A step-by-step evolution roadmap and understanding of present implementable solutions are presented. Finally, initiatives and strategies that need to be in place for different steps in the evolution path are laid forth.

3.4.4 Exploratory Data Analysis and Algorithmic Research

EDA and algorithmic research have been made for investigating further technical challenges found central to NLP applications in the NPP domain and text data analysis.

The first case of further investigation, analysis of masked event data and potential approaches, are motivated by the found limitations of sharing data between actors in the NPP domain. The second case, algorithmic research with semantic search and topic modelling of operation logs, is motivated mainly by the challenges associated to use state-of-the-art open source AI-models and the domain-specific language of the NPP industry. These use-cases of the model have been iterated together with a Swedish NPP actor for ensuring relevance.

Analysis of Masked Event Data and Potential Approaches

By collecting sensor data, e.g., time series data, predictive maintenance can be performed. Using recorded data of events with timestamps from sensor readings, the aim is to predict the type of incident that will occur at a certain time. More specifically predicting whether a machine will fail within the next 30 cycles has been investigated. The benefits are cost savings due to the maintenance frequency being reduced, as well as minimizing the amount of time spent on maintenance.

Algorithmic Research with Semantic Search and Topic Modelling of Operation Logs

From the information gathered from the interviews, themes of technical challenges and opportunities which were beneficial to investigate further were found. Data were collected from a Swedish utility for exploratory data analysis and algorithmic research. More detailed, data gathered from a Swedish NPP operation's logging system were used for Semantic Search and Topic Modelling using a state-of-the-art NLP model. Results were composed and insights were collected.

4 The Situation of Nordic NPP Industry

4.1 INVESTIGATION OF THE CURRENT STATUS

During most interviews, the conclusions made have been, that there is an interest in AI implementations, but few utilities have introductory programs.

The level of AI efforts varies between the Nordic utilities and the implementation of leveraging AI technology for component and/or sensor data analysis is the most common and of most interest to the Nordic actors.

One utility stands out in its efforts among the three utilities as they have come much further in their AI implementations of automatic sensor data analysis. To find deviations sooner, an AI solution has been implemented on the turbine side, using 900 analog signals to alarm before finding the deviations. To understand and interpret the output, good knowledge of the systems and facility is needed. The result which has been observed is that the system is not pushed/challenged as hard and fewer stoppages occur thanks to the AI solution, leading to more efficient use of resources.

Other applications that have been implemented are pattern recognition with process data and 360 deg cameras and video. Furthermore, unsupervised learning and clustering have been tested for applications, however, the area of application was not shared during the interview.

Many utilities are doing manual component and/or sensor data analysis, using different models of analysis, to gain insights into occurrences or events that have happened or to find trends in the data.

Some utilities have investigated potential AI applications for predictive maintenance and sensor data analysis through different types of intermediate projects, i.e. student thesis work or proof-of-concept projects. Two examples identified are the master-/bachelor theses that have been produced at the utilities on the subject, to the knowledge of the interview subjects. The thesis by Björn [9] investigated finding deviations in sensor data using AI. The thesis by Lindskog and Gunnarsson [10] looked at predictive maintenance. Machine learning was used to explore potential damage to machines based on measurements and historic issues of the machine.

There has also been an interest shown in predictive maintenance. It seems most organizations are focused on maintenance applications, but during the progress of the project, more and more ideas considering office applications have been presented by the project team members, which to most interviewees has represented a new way of thinking.

In the applications mentioned, some utilities mentioned investigations of SPOT-dogs from Boston dynamics, but there are still no defined applications for these sophisticated tools. It seems more like a representation of a research task without more advanced strategies to back it up.

Some utilities also look with interest to predictive maintenance functions implemented e.g. at Excelon. Such implementation for the Nordic NPPs however seems far away, as there are no central (vendor) locations where measurements from all plants are collected and used for evaluations.

There exists a lot of sensor data in the plants, both digital and analog signals indicating pressure, temperature, vibration, etc. The sensors are connected by wire. More sensors would be needed to facilitate proper predictive or condition-based maintenance, however, setting up new sensors connected by wire are costly.

Some organizations also recognize AI as a tool for competence expansion and recruitment. The problem many utilities point at is the lack of WLAN inside the facilities. In the case of AI solutions being proposed, a project for its introduction often needs to accept the cost of implementing a Wi-Fi network too. The network itself should not be too much of a challenge, but the validation process remains an unexplored territory.

In 2022, one utility is working on installing Wi-Fi at their facility. The project seems to run smoothly mainly thanks to the previous work of installing antennas, creating the possibility to use wireless phones on the facility with coverage all over the facility. Wi-Fi opens up for wireless sensors, which can lead to more sensors which is beneficial for AI solutions such as predictive maintenance. It also creates an opportunity for operators to use tablets.

A need and intermediate investigation for the creation of a "Data Lake" has been observed at an NPP, with the purpose to gain increased access to data, enabling further opportunities for creating a platform of analysis and results.

For the utilities, there are several challenges. In its nature of being a software function, AI will be restricted by IT-security measures, not only close to the main process, but also for office applications. In the background of these IT restrictions, there are often aspects of regulation, which often favor hardware-based applications.

Regarding applications for Optical Character Recognition (OCR), which focus on digitalizing physical documents, there are little to no handwritten nor physical documents where information is not depreciated in internal systems. In the case it does exist only in physical form, the documents have been identified as very old archived drawings of the NPPs, since the ones that have been in use already have been recreated into a digital format, or as documents that are not allowed to be digital for security reasons. Also, workers' printed instructions and associated notes have been identified to exist in the physical format before immediately being noted in the utilities' logging systems.

OCR has been used at some utilities to digitize old drawings of the plants in previous projects. Since there have been a lot of improvements in the performance of the technology, loose plans can be found aiming to iterate through similar projects again, since many digital images of old drawings or similar exist – but not in a digitized format.

There are no NLP solutions implemented for operation and maintenance purposes identified from the interviews with the Nordic actors. All utilities use the search functionality in their archives, intranet, or logs for finding information, although the quality of results or functionality varies. Other examples of where NLP solutions are embedded would be on the customer side, with examples like chatbots for customer services, etcetera.

Problematic cultural phenomenon, such as low trust in AI systems and low willingness for change, have been mentioned. Not much awareness or knowledge within the Nordic NPPs in the field of NLP could be identified. As the Nordic actors have not looked further into NLP, approaches on how to solve domain-specific issues have not been identified. However, some Nordic interviewees have confirmed that the nuclear language is very domain-specific, and can differ largely between utilities. Further challenges are that exists limited permissions, access, or quality of data.

Identified potential challenges for an increased level of data-driven maturity will be further elaborated in Section 8.

4.2 THE FUTURE AI PLANS AND/OR STRATEGIES

Strategies for digitalization have been identified, although no explicit AI-implementation strategy was identified at any utility. The project team would like to emphasize that AI could potentially be seen as a part of those plans or strategies – but occurrences of AI strategies have not been found in this study.

No explicit plan for developing use-cases or implementations using OCR or NLP has been mentioned. However many use-cases have been presented and identified to have much potential for the industry.

Many interviewees saw several future solutions within AI at the utilities. In summarization, most future solutions can be composed of going from a time defined to a decisive/condition-based maintenance system, as it is seen to be more resource-efficient. These solutions were seen to mainly use the automatic analysis of sensor data from different components for O&M, to increase the level to be predictive, and not be made regularly in time – since AI often is seen to be able to find information and draw conclusions of a larger amount of data than humans can.

Some other use-cases of AI solutions that were mentioned during the interviews were:

- To automatically generate work orders when sensors give out event- or condition-based alarms.
- Detect fatigue of workers, by identifying behaviors.
- Automatic analysis of surveillance videos.
- Automatic analysis of X-ray imagery in security check-points.
- Automize estimations of inventory and supply chain processes.
- Other computer vision (CV) applications or use-cases.
- In the main process itself, it should be possible to use OCR algorithms to validate fuel bundle ID before moving fuel in and out of the reactor core.
- In the office areas, the use of NLP-based Expert Advisors as pointed out in this report may be introduced.

- Control room and operator applications as well as competency-based assessments of NPPs, more can be found in Borgvall et. Al [1].
- Analysis of time-series data can be used to predict maintenance needs.
- Drones with face and pattern recognition software can be used to detect foreign material on-site and hostile break-through.
- Connecting existing process signals, such as video and measurements, to an AI implementation can facilitate building a fuel tracking function.

In terms of OCR, there has been shown interest in how workers and operators could search for components to find the archived and older drawings existing as digital images to them. OCR could be used to identify the components in the drawings. OCR could also be used in terms of identifying components or positions of the plant by text or identifier with the future use of Digital Twins. Earlier projects or attempts to digitize old NPPs' plans were also mentioned as fruitful to conduct once more since the development of that technology is seen to have come a long way in later years.

The most fruitful application of NLP has been identified to improve the internal search for information. Many times, difficulties to find information have been mentioned for novice users. With large amounts of information, it has been stated that it is important to know very well how and what to search for to find the correct information. The same application could also assist in finding the root of errors in reports and finding trends.

Another potential NLP application that has been identified would be to make the documentation process of the operation and maintenance more efficient by using speech-to-text, where workers can document with their voice.

Other technology developments which can serve in enabling a more data-driven operation and maintenance that have been identified, are:

- Installation of Wi-Fi and digitization of work orders, i.e. going from papers to getting instructions on a mobile device and improving information flow within the utility.
- Installation of Wi-Fi and wireless sensors at utilities, for increasing the numbers of sensors given that wired sensors are expensive and complex to handle.
- Creation of a "Data Lake" on utility level, with the purpose to gain increased access to data enabling further opportunities for creating a platform of analysis and results.
- Creation of Digital Twins of NPPs, which would improve the awareness and increase the accuracy and correctness of the plant's components, functions, and plan. Mentions of using Augmented Reality (AR) in association with the Digital Twin have also occurred.

The project team members hope this report will present several use cases for AI-implementations that can be implemented. The project team members are convinced there are several opportunities for the utilities to use and hope this report will seed the interest in applying strategic plans for the introduction of AI-applications not only in the main process but also for facilitation of Expert Advisors (EA's).

5 Survey of AI initiatives in NPP Industry

5.1 REPORT ON EFFICIENT AND SAFE AI APPROACHES FOR O&M

5.1.1 Choosing Explainable AI Models

Explainable AI is the contrast of AI models that function as a "black-box", in which it is possible to explain why an AI model arrives at a specific prediction or decision. This can assist in being more accepting of an AI model which can be beneficial when there are regulatory demands of the analysis which are to be made. It can also be used to confirm assumptions or knowledge as well as to generate new ones.

Although an explainable AI model could be a tempting solution, the effectiveness or performance of their systems can be lower than going with a model with more abstraction or complexity.

5.1.2 Towards Safer AI Implementations

In the training phase, while using a representative and trusted data set for training, different KPIs can be used for evaluating the performance and tweaking the functionality of the model which is being trained. One example is to limit the probability of using measurements for false positives, meaning that it is more important to be sure about certain positive results of analysis than to be more sensitive to a possible positive result.

At the implementation of a model, detection of security attacks should be considered. Using a 1-class-classificator that can distinguish between normal traffic and other traffic can assist in robustly handling new occurrences or attacks which have not already been seen from the training phase. Questionable traffic can be raised to experts for evaluation and manually added to the training data for improving the functionality. Worth mentioning is that this can function both for input data as well as output predictions with low confidence for ensuring full governance.

One of the simplest methods to classify is by using a threshold. Given a certain input or output, a threshold or several thresholds can assist in serving a limit and ensure governance of models, with use cases such as increasing a model's robustness in the output for confidence scores or integrity of input data to the model for security reasons.

Data flow and well-designed modeling of the data can assist in ensuring safer and more efficient AI implementation. Examples of those can be found in Section 7.4.2.

5.1.3 Human-in-the-Loop

When a model is trusted to make the analysis of data and provide experts with results to be interpreted, the model can often be seen as harmful. This can be done in parallel with normal investigations to provide more insights and confidence for both analyses. Promoting a model to provide recommended decisions or even further make decisions itself would for industries with strict regulations and limitations be difficult.

Given the "black-box" that AI models are often referred to, an expert or human-in-the-loop can ensure governance. If acceptable, the confidence scope of an acceptable result can be selected to slip through manual evaluation for automating resource-consuming processes but still ensure governance of the functionality.

5.2 AI TECHNOLOGY FOR NPP INDUSTRY

To investigate further how AI, OCR, and/or NLP can be used for documentation, operation, and maintenance, three international actors in the field of NPP industry and AI have been reached out to.

A short introduction of the international actors' background within AI is presented below, which will be followed by findings.

5.2.1 Investigated Actors of the NPP industry with AI Experience

EPRI

EPRI is the Electric Power Research Institute, based in the US. They have a lot of knowledge regarding the nuclear power plant industry and research how the nuclear power plant industry could be more data-driven. EPRI's standard way of working is to conduct research, obtain data and perform what-if scenarios to see what would be different if AI was involved, to finally compare the model with the current traditional approach.

Curtiss-Wright

Curtiss-Wright is a supplier to the commercial nuclear fleet. They supply hardware, products, software, and services. One example is monitoring and control systems. Since 2010, Curtiss-Wright is pursuing AI on their data and they see that data is the key to knowledge in the future. Moreover, data allows them to help plants make decisions and this is one of their most important topics.

NuclearN

The two founders of NuclearN previously worked at an American NPP, where in 2016 started a data science team, a time when the buzzwords such as AI, ML, and data science had not yet infiltrated the industry. The team generated a lot of AI ideas and put a few of them into proof of concepts and aimed to put the best ones into production. They faced challenges such as founding and people's lack of understanding of the techniques. However, they had a lot of successes. They later created NuclearN and now deliver software with AI and NLP solutions to American NPPs.

5.2.2 AI Solutions

EPRI does research on how the nuclear energy sector could be more data-driven and therefore suggest a tight collaboration between plants through data sharing and to develop the technical foundations for the application of AI as this is the key to success. There are three datasets that EPRI has put together and found very impactful within the nuclear energy sector: the NDE assessment dataset, maintenance dataset, and operational dataset [11]. EPRI aims to help accelerate the development and applications with research and projects. They are currently creating a platform and framework for external and internal communication and tools for future development. They have furthermore divided their projects into four broad application areas: insights – learning from the past, prognostics-anticipating the future, automation – increasing reliability and optimization – increasing efficiency [12].

EPRI on Insights

There exist thousands of years of accumulated operating experience in the nuclear industry. By applying data science technologies, historic data and experience could be used to improve operating and maintenance efficiencies, creating new best practices based on data-driven decision-making. In the insight application area, a proof of concept for an industry-specific dictionary for NLP has been developed, data mining of the work order database has been performed and an event management response tool has been implemented. There are plans to implement NLP using the dictionary on Corrective Active Program (CAP) data for insights.

EPRI on Prognostics

Predicting events, failures and assessing current asset conditions (for example remaining useful lifetime of machines or parts) could be leveraged by various data science techniques. Such tools could furthermore be used by utilities to plan maintenance and outage strategies and thereby reducing unexpected downtimes and minimizing periodic inspections. In the prognostics application area, a preliminary study of the application of ML to inform flow-accelerated corrosion (FAC) inspection schedule has been completed with positive results. This project is to be followed up with further development. A study of anomaly detection based on plant monitoring and diagnostic data has also been initiated.

EPRI on Automation

By implementing more automation solutions, one could get higher reliability with faster and safer implementation, leading to reduced radiation exposure and critical downtime as well as better day-to-day operations. This initiative could also lead to fewer human factor errors and personal safety risks by using data science technologies. Some examples of automation developments by EPRI are an online tool to implement automated detection of concrete damage, a tool for monitoring dry cask vent temperature remotely using paired thermal and visual images, and several auto-analysis Non-destructive evaluation solutions. Furthermore, EPRI will work on automated analysis of dissimilar metal welds and adaptive feedback welding.

EPRI on Optimization

Optimization can be achieved by fine-tuning plant operations such as inventory management, fuel cycle parameters, and outage scheduling more intelligently using data science. This can improve operations, plants, strategies, and decision drivers, leading to savings in more efficient operations. For example, EPRI has created a proof of concept AI solution for increasing supply chain efficiency to optimize inventory management and reduce costs. Methods to evaluate and optimize decommissioning scenarios have also been investigated.

EPRI on Non-destructive evaluation

Non-destructive evaluation (NDE) is a testing and analysis technique commonly used in many industries. NDE is very cost-effective as does not affect the tested component and one can find defects before they malfunction. It can be used to evaluate the quality of materials and components as well as for finding welding defects. EPRI has been conducting NDEs within nuclear power plants using AI and has found that it holds great potential! Three main areas where AI can be a very powerful tool are Automated analysis of NDE inspection results, analysis of real-time NDE monitoring, and informing inspection planning through assessment of NDE history. AI has the potential to improve reliability and reduce the time required for NDE inspection data analysis. To achieve the full potential of these solutions, all nuclear stakeholders need to collaborate and share data as data from only one plant will not be enough to train a robust model [11].

Currently, EPRI has two deployed solutions, both within non-destructive evaluation. The first solution handles concrete structure inspections. Utilities can upload pictures of their inspections and run through the model to find defects. It is not yet deployed in real-time as EPRI is looking to find a site to host the demonstration, but it is ready for deployment. The second solution is automated analysis for ultrasonic inspection. It has been deployed and has shown very positive results.

Curtiss-Wright and NuclearN

AI has been applied to low-risk situations at Curtiss-Wright. For example, it has been used for categorization of text data as well as automating manual tasks which use many man-hours, like screening error data for categorization or data analysis.

NuclearN has tried supply chain optimization and forecasting for nuclear and networking graph analysis for issue detection. The two founders have worked on many other potential AI solutions as well, however, not all are mentioned in the interview.

5.2.3 NLP Solutions

The most common NLP solution mentioned by all three actors is NLP CAPs. In the US, all NPP:s have to run corrective action programs by law, however, there are no regulations on exactly how it should be performed. CAP can be described as the system for how a utility should find and fix problems at the plant. For example evaluating the safety significance of problems, setting priorities in correcting the problems as well tracking the problems until they have been corrected. CAP is a very time-consuming, expensive, and manual process in the US, which includes many persons and processes within the plant. Since the process is very standardized, both the inputs and outputs are well defined at each utility and have been for many years, leading to a large amount of quality data, perfect for AI to build upon and use for automation.

An approach that worked well for NuclearN was to list ideas and small use-cases that were analyzing data and assisting in parallel normal operation and business processes and filter out what use-cases were seen as feasible and viable given technical, safety, and regulatory limitations. Quickly, NuclearN and the NPP actor they were then currently working with were able to put together 20 ideas. Out of those, 6 were picked for making a small Proof of Concept to see what worked well. This portfolio concept of small and narrow applications assisted in a better chance to find things that could work in the NPP. One of NuclearN's many NLP solutions is corrective action program screening automation, which has been very successful. The solution incorporates NLP solutions, using some state-of-the-art transformers model, to screen and classify the CAP entries. The process includes a human in the loop as well which is important for the nuclear power plant industry to trust the process. The parameter for the threshold limit of accurate prediction has been set quite high, meaning that any uncertainties are double-checked by personnel, leading to few errors in the process.

Curtiss-Wright describes how they have looked at NRC's inspection procedures and compared them with all their regulatory data for that period. By crosschecking the two, using NLP and some more in-depth analysis, they identified potential issues. This led to the preparation process being shrunk and issues that a human analyst could not identify were found. When comparing an AI to an analyst in finding the issues there was some overlap, but mostly, the AI found more issues that utilities could prepare before the inspection.

EPRI has attempted to make use of free-text maintenance data using NLP on a large unstructured dataset, similar to the efforts in this project. They found that it was a challenging project and did not continue on that specific approach. They are now looking into text mining, trying to identify components that cause more problems to see if they can find correlations. For example, if one component breaks down, are other correlating components breaking down?

Furthermore, when asked regarding their efforts within using NLP for predictive maintenance, EPRI said that it would possibly work and they have had efforts investigating it in a fossil plant. They are using text mining to predict the remaining life of components. At a later stage, they will bring it over to the nuclear power plant industry.

Furthermore, NLP can help by looking at it holistically, finding trends, and finding out what one can do with the data.

5.2.4 Domain Specific Language Issues and Approaches

NLP has been used extensively at Curtiss-Wright as there is a lot of document data, but the formality of the data makes it hard to work with. The language is very special and words can mean very different things from everyday language as well as between power plants. An example is the term "Design-based Accident (DBA)". It has a special meaning and should be seen as one word, but NLP algorithms could try to interpret each word by themselves. For such reason, Curtiss-Wright has been working on creating a dictionary as well as tweaking the applications because of special lingo. However, creating a dictionary like this takes a lot of resources. The dictionary is not used for NLP applications today and hasn't been used in NLP applications in the past either. However, the dictionary has proved useful for new employees to get a much faster learning curve of AI models as they can understand the industry faster by studying the dictionary.

In recent years, it has also come to EPRI's attention that a dedicated vocabulary/dictionary could improve the NLP models in the nuclear domain. EPRI is asking themselves, which model to use and how much one can do without a dedicated vocabulary. Their first attempt at creating a dictionary for one specific use case was a successful project and they are expanding it for more study cases. More information can be found in their brief on the subject [13]. However, they still don't know how it would be applied in NLP models.

NuclearN, who has a lot of experience in applying NLP in the domain, was asked questions regarding what is the best practice for NLP within the domain. The interview subjects indicated that domain-adaptive pre-training (DAPT), which is described in Section 5.3 in Appendix B, is a good practice to tackle domain-specific issues, as well as domain-specific fine-tuning. Furthermore, they also implied that the idea of a dictionary is outdated, since domain-specific tokenizer/vocabulary is more relevant for state-of-the-art models, such as can be seen in SCIVOCAB [14], see Section 5.3 in Appendix B. Furthermore, one can add specific tokens to a tokenizer as well.

5.2.5 Data Availability

Data is crucial for creating AI and NLP solutions. NPP industries have regulations for saving data to a relatively great extent, which brings opportunities for the technologies.

Curtiss-Wright has created a large dataset of about 25 million data points from over 40 years due to its collaboration with many utilities. It consists of both sensor data and document/text data.

EPRI is making large efforts in data-driven decision-making and is therefore creating large datasets for the nuclear power plant industry in collaborations with utilities. Three large datasets that they have found to be very important for the industry are the non-destructive evaluation assessment dataset, maintenance dataset, and operational dataset. The maintenance dataset contains millions of records, it's semi-structured, so there are some structured fields, such as costs and categories of maintenance. There also exists unlabeled free text data, similar to the data collected in this project. Unfortunately, EPRI did not manage to get any valuable output in their first attempt at analysis.

The team of NucelarN previously worked at a power plant, where they had access to data during that period. As they have several customers in the US, they work with their customers' data. As data is sensitive, it's common that their solutions are implemented on the premises.

5.2.6 Future of AI

According to our interview subject at Curtiss-Wright, people have been more open to AI within the last 2 years, partly because of Covid, as people had more time, and discussions regarding AI have therefore come up at conferences and the Nuclear Regulatory Commission (NRC). Curtiss-Wright sees a lot of potential within AI, but it is important to mix human interaction with AI because AI can't as of now be completely trusted within this industry. Our interview subject suggests investigating different NLP tasks and finding the ones which will give the most efficient output. Administrative tasks, as easy as literally moving papers and documents would be good implementations. In maintenance, better data collection instead of humans going out and collecting the data would open up a lot of doors for AI. According to the interview subject, advanced reactors and Small Modular Reactors (SMRs) are trying to take advantage of these newer technologies as they will have fewer people operating them and thereby need more data-driven decision-making.

EPRI is working towards a more data-driven industry and suggests more data-sharing initiatives and collaborations between utilities for faster development within the industry.

5.2.7 Challenges & Lessons Learned

To implement predictive maintenance, one would need many more sensors in the NPP. Furthermore, data sharing and data access within the utilities seem to be an issue, as well as data sharing between utilities and external parties. AI has not been very trusted and people have been skeptical in the past. For example, engineers often want to understand how things work but that is a challenge because AI often is like a black box.

NuclearN states that many utilities think that they can build automation using AI themselves and according to them they do – as long as the utilities have the right competence and management. The differences between actors that have succeeded and the ones that do not, are the obtained performance of the AI models and change management. Regarding performance of the AI models, are there many things included for ensuring functionality that often is not thought of, like threshold management, risk automation trade-off, auditing, etcetera. About change management, utilities that do not recognize the challenges associated to the adoption of data-driven techniques run into resistance. On that note, they have experienced that change needs to be adopted incrementally, in small steps, rather than in radical steps. Furthermore, NukelearN states that they have experienced that NPP utilities and workers prefer simple automation of existing processes rather than large software packages that change what they currently are handling processes or doing, even if the change would be an improvement for the better. In some cases, NuclearN's proposed improvements would be ignored or refused to be adopted, even if they improved their processes significantly, but especially if it changed the way that they were currently doing their job.

NukelearN states that for modern NLP techniques and models, there is no need for something like a NPP dictionary while using modern NLP models – since modern

NLP models have a higher level of abstraction than more expert based models and use tokenizers. In the case of using models with less abstraction, such as Random Forest or Decision Trees, then it would be necessary. AI explainability of models was more important when the models were having worse performance. At that time, there was sought a need to control the input with something as a dictionary.

The quote below embodies one of the difficulties of AI model abstraction, or the trade-offs between using explainable AI versus black-box AI models.

> *"But you end up in a paradox, though, because the models suck too bad actually to be used to do anything real... But they're explainable. So you're just explaining to somebody why these models suck, right? Or aren't very good. And that's not very useful from a business perspective. You need a black box model that delivers…It's just an emotional thing, right about has to be... it actually runs back to the question whether the person can do the explanation, but how does the person work? How does the brain work? Nobody can answer that... if you go to human psychology and you just look at research about how people explain how they come up with the answers, they almost always their train of thought or how they think they came up with an answer is almost always not actually how they did it…So it's like, you know, when you ask a human, they don't do it very well. So if you we always like to say, use your human as the benchmark, right. Don't try and evaluate this like, AI technology as this own new thing, just like, treat it as if it was another person working alongside you. How would you assess the results right now? How would you do this? How would you have them explain it? And would you get people in the right mindset and a lot of it goes back to change management."*

- *NukelearN*

More challenges that have been learned in the processes:

- The domain-specific language.
- There are difficulties to improve model performance without sharing data between utilities, since the performance and the robustness of AI models improves greatly with more and more diverse data. NuclearN states that one of the primary reasons why the CAP use-case is working well is because all the utilities do the same things.
- NuclearN found challenges even with moon-shot use-cases, experiencing that they often were years ahead of the level of data-driven maturity as to what was needed. Therefore, change management and education are important in the process of increasing the change of being able to test, implement and use the technology.
- Utilities want small (complex) automation of existing processes rather than large software packages that change how they work. Those radical changes have not been well received, they have been quite ignored. Moreover, working with anything safety-related is a hassle. Therefore, focusing on more administrative tasks could be a better way to go.
- Some state-of-the-art models such as GPT-3 can't be used as the solutions have to be on-premise due to security risks.

- Change management and education are important for AI to be implemented, it needs to be done incrementally, with small steps, and people need to be further educated on the subject. Managers need to understand the requirements and resources needed for a transformation. Workers need to trust that they will be assisted with and not be replaced by automatic processes.
- Labeled data can for some use-cases be hard to come by, making implementation of NLP more challenging.

6 AI initiatives in the energy industry and in other industries

6.1 AI INITIATIVES IN THE ENERGY INDUSTRY

AI in the energy industry will play a more important role when the diversity of energy sources rice. Renewably energy sources like wind power and sun energy spread over big geographical areas is challenging the old energy distribution grids and the old business models for selling energy. AI will have the same importance in these areas as it has in the financial market, e.g. stock markets. In this section we briefly discuss some important initiative in the rapidly changing energy sector. The examples are collected from multiple sources. Other public studies, articles and other AFRY project are used as sources.

Demonstrating AI and to exemplify the practical use of NLP, the three chapters following have been analyzed using an NLP technique called Topic Analysis, described in Appendix D.

6.1.1 AI in the Power Grids

The power grid is facing new challenges. The rapidly expansion of wind power and solar energy are putting new requirement on the power grid. The power grid is built for few and big power sources, like water and nuclear power. The balance in the grids is much more difficult to maintain when the number of power sources increases and when the power sources is more geographical spread. Especially when the new power sources are whether dependent. Less wind, less power. The risk of power outage for the consumers increases if the balance in the grid can't be maintained. With self-learning AI-algorithms it could be possible to predict power production and power usage and thereby give the power grid operators tools to maintain the balance in the grids and secure the power distribution. One example of an IT-tool, probably with some AI, for optimizing the use of the power grids is SWITCH from EON. SWITCH is a digital marketplace where both energy producers and consumers interact so grid owners can predict and handle power peeks in the grid.
A couple of articles by Jim Magill, Forbes [15], Jian Jiao, IOP Conference [16] and Veritone [17] on AI in power grids were analyzed and resulted in the following brief statements on AI in power grids:

- With electricity market reform and the application scenarios of renewable energy and power demand response, the power system presents the characteristics of openness, uncertainty and complexity.
- There are corresponding application scenarios of AI in every link of power system, such as power generation, power transmission, power transformation, power distribution and power consumption.
- Although the application of AI in the smart grid faces many problems, such as insufficient data sample accumulation, insufficient reliability, imperfect infrastructure, lack of special algorithm for power industry, etc., on the whole,

AI is a powerful tool to push smart grid into the new generation of power systems and energy networks.

- The increasing scale of the power grid, the access of renewable energy power plants and the reform of the electricity market make the power system increasingly complex, which brings a lot of uncertainty the operation of the power grid.
- In smart grid, self-repair control system can automatically diagnoseand recover, quickly restore power supply, shorten power failure time, reduce power failure frequency and power failure range.
- Scenarios of AI in smart grid include power supply, power system optimization, power user behaviour analysis, fault diagnosis, etc.
- Another AI application, developed by an AI software company, helps lower the carbon emissions of a power grid by reducing the amount of fuel that you need to power the grid by 8%.
- There are flexible power equipment in alternating current transmission, direct current transmission, renewable energy generation, power storage, power distribution system, micro grid and other fields.
- From the point of view of the power grid manager, effective management of user demand can help balance the power supply and enhance the reliability of the power system.
- Because power generated by wind and solar energy is usually cheaper than power from natural gas-fired plants — as well as having greater climate benefits — grid operators tend to rely on these forms of renewable energy as much as they can.
- Forecasting power load makes power production and load match in real-time, which becomes the important work of power grid daily operation.
- When the power grid continues to produce a large number of high-dimensional and multi-type data, the traditional modelling, optimization and control technologies have many limitations, which put forward higher requirements on the power grid.
- The application of new materials, energy storage technology and information technology, as well as the support of two-way flow of electric energy, makes smart grid have stronger resource allocation capacity and support the access of large-scale renewable energy generation.

6.1.2 Wind Power Industry

A couple of articles by The Agility Effect [18], Elektroniktidningen (SE) [19] and Wind power Engineering & Development [20] on AI in wind power were analyzed and resulted in the following brief statements on AI in wind power:

- Be sure to look for a system that is supported by wind industry domain experts, as the combination of data science expertise and wind industry expertise leads to the best outcomes.
- By using artificial neurons that predict the weather, and weigh it together with the turbines' historical production, a wind farm in the USA has been able to predict wind power production 36 hours in advance.

- The best definition of artificial intelligence is that it is set of methods or algorithms that use a large amount of data to learn rules or patterns, and continuously improves with additional data.
- The sources from which AI can pull information may include:
  · SCADA data (mean, minimum, maximum, and standard deviations),
  · Maintenance data (component replacement dates, lubrication events, etc.
- Whether we talk about wind, solar or hydropower, all three are dependent on the weather, and therefore the power and analysis capacity of digital systems is very important.
- Failure histories, Firmware updates, CMS data; These data sources are used to create models of normal turbine behavior, which serve to quickly identify abnormalities and notify the wind-farm operator.
- One of the best examples of AI use cases is automated detection of yaw misalignment, which, if left undetected leads to lost energy production and increased loads on the turbine.
- The DeepMind example shows that the models that make it possible to interpret weather forecasts to predict production are becoming increasingly advanced, thanks to AI.
- The next step in productization is to seriously dig into the economic conditions for the new way of working with maintenance of wind power - what are the costs for a new way of working, and what will it mean for savings for the industry?
- The methods are based on artificial intelligence and on analysis of large amounts of operation and maintenance data from wind turbines.
- The models monitor a turbine 24 hours a day, seven days a week, and relieve human operators of the tedious task of sifting through extremely large data sets in search of relevant insights.
- One of the challenges is that operation and wear at wind turbines are affected by the external conditions, which means that no wind power installation will be the same as the other.
- Forecast systems for renewable energy production based on artificial intelligence are continuously improved, making integration into the global electricity grid easier.
- Given how unpredictable the production of renewable energy has been, the ability to predict produced megawatt hours provides great added value.

6.1.3 Hydro Power Industry

A couple of articles by Vattenfall [21], Uniper [22], and Mäladalens University [23] on AI in hydro were analyzed and resulted in the following brief statements on AI in hydro power:

- At Mälardalen University, research is underway to improve the production and storage of hydropower with the help of AI and Internet-of-Things (IoT).
- Remote sensing can help solve the problem of unknown snow volumes by using large amounts of data from different satellite platforms together with AI and IoT technology, which can create new opportunities for hydropower plants to gain a better understanding of the amount of snow.

- Water from melting snow and the spring flood are important sources for hydropower production, and therefore it is important to be able to measure and estimate the volume of snow cover to be able to plan the production of hydropower but also prevent flooding.
- The hydropower plants of the future are connected and smart devices continuously supply development teams to develop digital solutions to improve operations in hydropower, a work that takes place in close collaboration with those who work with operation and maintenance of power plants.
- The algorithm will also be trained in distinguishing between salmon and trout, determining the size of the fish and possibly also including more species and identifying returning individuals…
- But hydropower within Company is not just a source of renewable electricity, there is also another power here: an effort to find new smart solutions with digital technology and new ways of working.

6.1.4 Challenges and Lessons Learned from this AI Initiatives

It seems in most industries there are "islands" of AI implementations but rarely is any company found with a strategy for a full-scale implementation of AI solutions and functions. Also, every company investigated is looking into technical solutions, mainly considering remote operations and maintenance, while rarely any companies are looking into AI-based Expert advisors or AI functions to detect human misbehavior.

These findings are not at all surprising since and as sometimes pointed out, the field has seen starts and stalls, as many of AI's successes have been promising for research progress, but haven't necessarily translated into applications for businesses.

A finding by the project team, e.g. while putting together the Rome presentation in appendix C, was that no AI function was ever found integrated with an existing automation process. Instead, in every application, AI functions have been used as stand-alone "tools" used to enhance a specific process step instead of being strategically integrated into a full-scale automation process.

6.1.5 iFTF – AI-based Fuel Transport Function

As an example of use cases applicable to the nuclear industry, the team is putting together a use case presentation of a fuel tracking function based on two videos released on YouTube, Describing an encapsulation process of spent nuclear fuel. To be presented at the EPRI AI and Electric Power Summit in October 2022, see the preliminary presentation in Appendix C.

That presentation will not touch upon the EA's suggested in this report.

The case study revolves around a proposed tracking function, called iFTF (AI-based Fuel Transport Function), that in real-time tracks each spent fuel bundle from the interim storage in Oskarshamn Sweden to the final repository in Forsmark Sweden, supposedly by using existing installations in the encapsulation facility (under design).

The presentation points out which AI-based functions can be used along the encapsulation process and which functions are advanced software only, based on signals implemented in the normal processes. All suggested use of existing signals will be used with isolation devices in order not to challenge the facility's integrity, and all software signals will consider strict IT-security restrictions.

Combined, the traditional software and the AI functions will show how it is possible to create the iFTF function, a redundant fully integrated AI-automated fuel transport supervision application.

6.2 AI INITIATIVES IN OTHER INDUSTRIES

In this section we present some example of AI initiatives from industries other than the energy sector. All examples are from projects and studies conducted by AFRY.

6.2.1 AI Agent for Energy Systems

A possibility to bring together energy-saving services and put them as one unified digital platform. This approach addresses multiple scenarios, which are listed in this section.

Reactive systems

Traditional Heating, Ventilation, and Air Conditioning (HVAC) systems are reactive to the current energy needs instead of being proactive. Changes in the HVAC system mitigate slowly throughout the building due to its thermal inertia (> hours).

By integrating AI system with traditional HVAC, the resulting energy system becomes proactive and can plan ahead for the upcoming energy needs. This is due to how system predicts upcoming changes, using AI. This also overcomes the problem with the thermal inertia.

User loads

Traditional HVAC reacts poorly to the user loads, since the presence of inhabitants is poorly measured. AI system predicts the user loads and also refines these predictions over time, by learning the user patterns of the inhabitants.

The use of weather data

Traditional HVAC uses the current outdoor temperature. It does not plan ahead for temperature changes but uses static schemas (i.e. night schema and day schema).

With AI system the upcoming weather changes are predicted using a combination of external weather data and the external temperature sensors of the building.

Crowd sensors are acting too late

In buildings (and similar) there are often CO2 sensors present in the rooms, to react when a room is crowded and increase the ventilation. From a user perspective, this typically happens too late, the room is already warm and muggy. This leads to poor comfort.

By combining traditional HVAC with AI System, each room can immediately request changes to the HVAC system, according to changes in the number of persons present. This ensures good comfort irrespectively of how rooms are used.

Irregular use of office spaces

In buildings the user patterns typically change and evolve with time. This often results in rooms being empty for long periods of time while other rooms may have an increased presence.

Traditional HVAC does not follow these changes, due to 1) lack of sensors for measuring people and 2) the reactiveness of traditional HVAC. By combining AI systems with our AFRY Flagship product, Flowity sensors, the user patterns can be predicted. Energy can be saved proactively in unused rooms while the comfort increases in other rooms. The AI system learns new user patterns and forgets patterns which are no longer present.

6.2.2 Automotive Industry

When it comes to production and procurement systems in the automotive industry, examples opportunities for immediate AI implementation are some of the following.

Spend classification and enrichment

Several AI techniques are commonly used in spending classification algorithms. Simple versions of these tools search through line item details and flag keywords associated with categories of spending. Utilizing NLP, they link input variables, such as account descriptions and supplier names. Next, the output is classified based on machine learning.

Global sourcing insights

Data is aggregated and analyzed using AI to determine the effectiveness of different sourcing strategies. Publicly available or licensed data can be used. These tools can provide insight into future trends and inform the sourcing strategies for a variety of product categories using econometrics to identify shifts in global supply.

Invoice data extraction

Depending on the provider, this technology can be integrated into existing systems or accessed via an email attachment with all relevant fields extracted in 30 to 60 seconds. Invoice data can be extracted using a combination of CV and NLP.

Automated compliance monitoring

These tools are able to automatically compare payment terms, identify differences between rates in a contract and an invoice, and identify duplicate invoices based on the techniques described in headings 1, 2, and 3. The current market solutions for AI offer transformational opportunities, but they are not yet mature enough to become concrete products. Therefore, these solutions are generally more valuable when applied to a specific business problem. Audits of expense receipts and service provider invoices are examples of audits to ensure compliance.

Contract data extraction

All contracts must first be collected in electronic format by an organization. A document's images can be converted to a text format using optical character recognition where it is appropriate text format. NLP is then used to analyze the text. It is generally the case that the contracts analyzed using this technology are in unique formats and templates based on the procurement practices of an organization. To use the models on other contracts, users must train them by annotating examples in a user interface.

Contract lifecycle management

By standardizing templates, automating first drafts of agreements, and managing the workflow throughout the negotiation process, the most successful solutions reduce cycle time and streamline the contract management process. A full audit trail that includes the appropriate approvals and escalations can be provided by consolidating all executed contracts in one place. By using NLP, these tools can assist contract managers and legal in identifying contract language that differs from the company's policies, allowing them to review the most pertinent clauses.

6.2.3 Process Industries

In some cases in the process industries, the use of optical sensors, OCR, and other AI applications to assist in monitoring analog indicators, dashboards, critical components, or evaluation in the processes.

Since the analysis can be made in near real-time or in real-time, the analysis can help detect defects, warn on given trained occurrences of events, or image signalment in the same fashion as a human can observe from their eyesight. This reduces the resource-consuming tasks of workers to manually evaluate, continually observe, or do checkups.

Automatically knowing exactly what has happened is not always essential. Knowing where to look can often save many resources and decrease human mistakes, before being further examined by humans.

7 Opportunity Analysis

7.1 INTRODUCTORY NOTES ON THE PROCESS OF MAPPING TECHNOLOGIES, PRODUCTS, AND SOLUTIONS TO NPP INDUSTRY

Among existing technologies, products and solutions within AI, a multitude of applications and use-cases can be made useful for the nuclear industry. To ensure governance, safety and efficiency, the solutions or applications needs to be designed, modelled, developed and tested for the respective use-case or domain.

In this section, presentations of efforts to show feasibility will be presented followed by a discussion mapping the technologies to the NPP industry.

7.2 EXPLORATORY DATA ANALYSIS AND ALGORITHMIC RESEARCH

EDA and algorithmic research have been made for investigating further technical challenges found central to NLP applications in the NPP domain and text data analysis.

7.2.1 Analysis of Masked Event Data and Potential Approaches

Analysis of masked event data and potential approaches, are motivated by the found limitations of sharing data between actors in the NPP domain, which would improve robustness and performance of AI models.

Sensor data are collected for the purpose of predictive maintenance. Typically, time series data are used for predictive maintenance.

An identifier for each device is included with a timestamp, a set of sensor readings collected simultaneously with the timestamps, and a timestamp. Using the data collected up to that point, the goal of predictive maintenance is to predict the type of incident that will occur at time "t".

Sample data were analysed, and with respect to different timestamps, events were recorded in two classes “Försvinnande” (“Disappearing”) and “Kommande” (“Upcoming”), and whether it is a repetition, “R”, or not. The data are masked because of a non-disclosure agreement. Furthermore, the recorded data consist of 4168 events in 174500 timestamps, see Figure 3. Figure 4 and Figure 5 illustrate event count by time, and event by day respectively.

Timestamp	Event Name
2020-05-31 00:23:21.134	Event 1 Försvinnande
2020-05-31 00:23:29.354	Event 2 Kommande
2020-05-31 00:23:29.399	Event 3 Försvinnande
2020-05-31 00:23:30.384	Event 3 Kommande R
2020-05-31 00:32:01.794	Event 5 Kommande
2020-05-31 00:32:13.432	Event 5 Försvinnande
2020-05-31 00:33:25.717	Event 5 Kommande R
2020-05-31 00:38:48.029	Event 5 Kommande
2020-05-31 00:39:13.505	Event 5 Försvinnande
2020-05-31 01:14:49.899	Event 6 Kommande
2020-05-31 01:14:52.006	Event 6 Försvinnande
2020-05-31 01:14:53.031	Event 6 Kommande R
2020-05-31 01:16:11.638	Event 7 Kommande
2020-05-31 01:16:56.728	Event 8 Kommande
2020-05-31 01:17:02.187	Event 8 Försvinnande
2020-05-31 01:17:42.644	Event 7 Försvinnande
2020-05-31 01:17:48.277	Event 6 Försvinnande
2020-05-31 01:17:50.359	Event 7 Kommande R
2020-05-31 01:17:55.151	Event 6 Kommande R
2020-05-31 01:18:01.440	Event 9 Kommande
2020-05-31 01:18:06.178	Event 9 Försvinnande

Figure 3: Recorded event data with the classes "Försvinnande" and "Kommande".

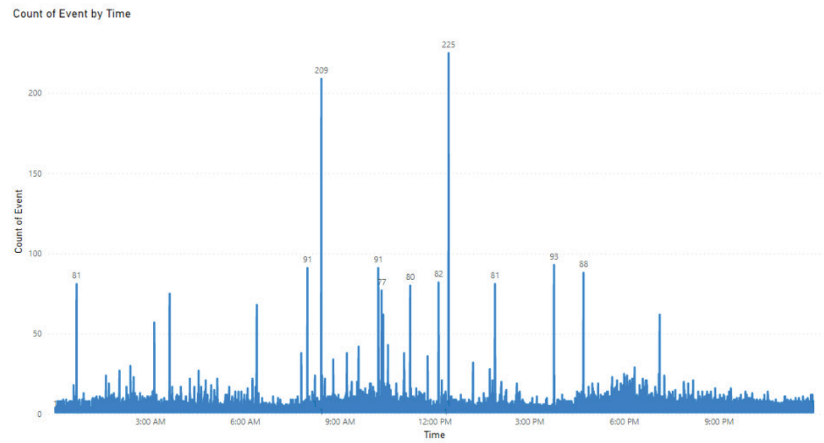

Figure 4: Count of event by time.

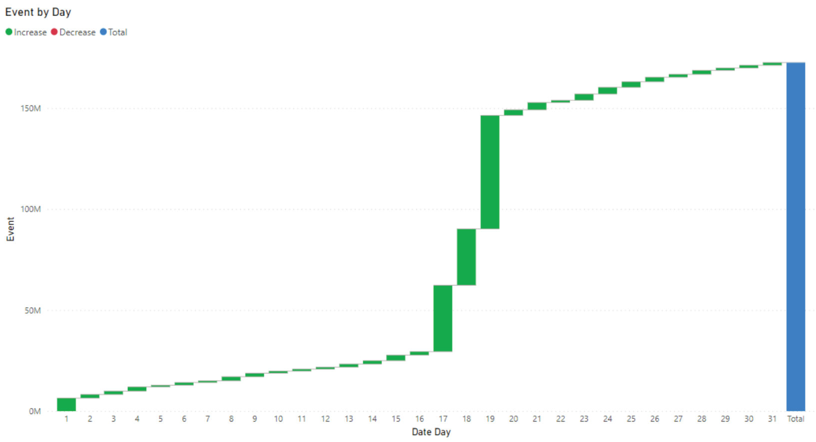

Figure 5: Event by day.

There are two approaches to predictive maintenance:

1. A classification approach that predicts whether any event will occur in the next n steps.
2. An approach based on regression, which predicts how long it will be before the next event. This is called the Remaining Useful Life (RUL). This can provide greater accuracy with less data than the former method, which provides only a boolean answer. However, it provides more information about when the event will take place, even though it requires more data.

Predicting RUL with Regression

When predicting RUL, the goal is to reduce the error between the actual RUL and the predicted RUL. Root Mean Squared Error will be used here, since it penalizes large errors severely, which will force the algorithm to forecast RUL as close as possible:

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad y_i = \textit{predicted value},\ \hat{y}_i = \textit{actual value}$$

An example of a prediction pipeline can be seen in Figure 6. The first step was to run the pipeline with only highlighted steps to get a sense of what is possible. By doing this, the algorithm is run without feature engineering.

Phase 1: Model Selection

A model selection pipeline for predictive maintenance is shown in Figure 6. In this example, only the dark-colored steps of the pipelines are used.

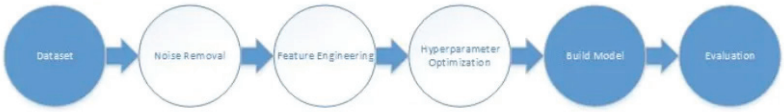

Figure 6: A model selection pipeline.

To capture and unmask the parameters of the event, a wide range of regression algorithms from scikit-learn and H2O have to be used. Deep learning is achieved using the H2O Deep-Learning algorithm, which can be used in both classification and regression applications. A multi-layered feed-forward neural network is used that is trained with stochastic gradient descent using back-propagation.

Phase 2: Removal of Sensor Noises Using Auto-Encoders

Sensor readings are often noisy. To eliminate this noise, we use autoencoders. An autoencoder is a simple neural network trained using the same dataset as both input and output, where the network has fewer parameters than the dimensions of the data set. The principal component analysis (PCA) (http://setosa.io/ev/principal-component-analysis/) represents data in terms of its principal dimensions. Noise has a much higher dimension than regular data; this process reduces the noise.

Possibly, an Auto-encoder with three hidden layers need to be used.

Phase 3: Feature Engineering

During this step, many features are tried out, and only the ones that are the most predictive will be kept. Time-series data are auto-correlated in the dataset, and hence readings are correlated. As a result, it is possible that prediction at time "t" is affected by a time window before "t". Most of the features used are based on these time windows.

Phase 4: Using grid search to optimize hyper-parameters

The algorithm is controlled by hyperparameters. Finally, the following hyper parameters: epochs, distribution, activation, and hidden layer size can be optimized.

The next step is to predict an event in the next N steps by building a model. In this method, whether a machine will fail within the next 30 cycles will be predicted rather than providing the number of remaining life cycles. Failures are considered positive (P) and no failures are considered normal (N). After this, a confusion matrix is plotted.

Overall results in several costs savings:

1. Reduces maintenance frequency.
2. Optimizes the use of maintenance time by minimizing the amount of time spent on specific equipment being maintained.
3. Reduces the cost of maintenance.

7.2.2 Algorithmic Research with Semantic Search and Topic Modelling of Operation Logs

Algorithmic research with semantic search and topic modelling of operation logs, is motivated mainly by the challenges associated to use state-of-the-art open source AI-models and the domain-specific language of the NPP industry. These use-cases of the model have been iterated together with a Swedish NPP actor for ensuring relevance.

For the case of exploratory data analysis, NLP techniques have been used to investigate how text data can be analyzed and utilized to aid operations and maintenance in the Swedish NPP industry.

Operations logs – the data of choice

The logging system is similar to a diary or bulletin board of operations at this NPP. Operators such as Turbine operators (TOP), and Reactor operators (ROP) document what has happened throughout the day, which is noted as free text on a computer by the operator.

The logging system is used by specialists to analyze different anomalies and malfunctions at the power plant. The specialist searches for a keyword to find a happening and tries to find similar happenings with the keyword, as an example.

BERT – the AI model of choice

The state-of-the-art transformers model BERT was used to analyze text data from operation logs. BERT works on many different NLP tasks and is a pre-trained model, meaning that the user doesn't have to train it from scratch. As the size of the data acquired was relatively small, a pre-trained model was a requirement as it's difficult to train on the available data. As the data is considered to be sensitive, BERT was a good choice since it is a local and open-sourced model which can be used for on-premise solutions.

BERT is a very versatile NLP method on which much research and tweaks have been done. BERT has been used for several domain-specific areas such as nuclear, biomedical, and clinical domains.

Furthermore, in recent years, Swedish BERT models have emerged. BERT can be used for a variety of language tasks, such as sentiment analysis, question answering, text prediction, text generation, summarization, etcetera. These components, as well as being an open-source model, makes BERT a strong candidate to use in the nuclear power plant industry to solve NLP tasks.

Method of exploratory data analysis

Exploratory data analysis was made on text data from the earlier mentioned logging system. This data was made avaliable from a Swedish NPP. Some intermediate results are shown below.

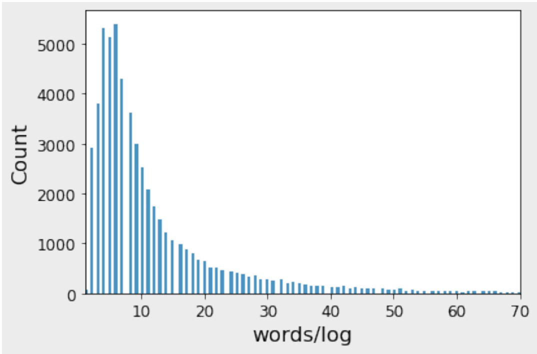

Figure 7: A visualization of the length of the logs up to 70 words.

Observing the number of free text words in the logs in Figure 7, one can see the most common length of the text logs is somewhere between 1 and 20 words. The mean was calculated to be 12 words and the median to be 8 words. The longest log was 422 words.

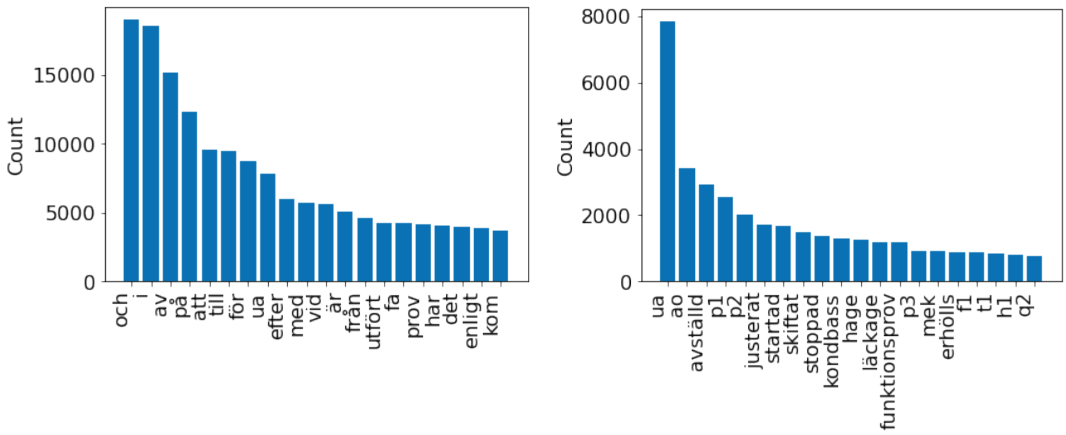

Figure 8: To the left (a) many stop words can be observed. To the right (b) after removing the stop words and using tokenization, another result is obtained.

Investigating further the content of the data, many stopwords were found (see Figure 8 a). By further processing of the tokenization, removing common Swedish words for a better understanding of the dataset and the occurrence of nuclear-specific words could be obtained (see Figure 8 b).

As the contribution of the log comes from a large range of operators over a longer period, the logs can differ in language but have the same meaning. Since the data are unlabeled, expert input from the nuclear domain is required for a proper analysis of the results.

Working with unlabeled data, statistical representations and clustering are standard practices. Given that the data is in free text, the data is unlabelled and using the insights gained from the interviews with the Nordic NPPs – two use-cases of using the models were chosen. These were:

- Semantic Search - finding the most similar logs, given a chosen log. The score represents the similarity calculated by the cosine similarity, i.e, how close in the angular distance the embeddings are to each other.
- Topic Modelling – dividing the data into clusters and assigning them topics based on the most important words.

Some representations of the results

In Figure 9, it is possible to observe significant results of the semantic search of a log and how that search is similar to the latest 600 samples of logs. How well the sentences are embedded to capture their semantics is a difficult task to evaluate when there is no ground truth, labeling, or supervised learning.

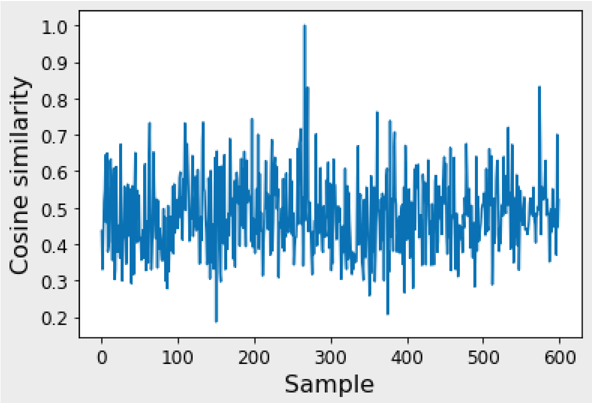

Figure 9: A visualization of cosine scores for in time newest 600 samples. The sample searched for can be observed to reach the value of 1.0 (around sample 260). It is possible to observe a similar log of high probability around sample 575.

In Figure 10, one can get a sense of what the largest clusters of the dataset contain. In the figure, we can see themes such as alarm, valve, leakage, and canceled/shut down (Swedish meaning: avställd).

It is difficult to assess whether the topic modeling and clustering are performing well. The reasons for that are the same as for the similarity search. It's also challenging to evaluate if the amount of clusters is optimal or if it should be reduced or increased. An expert who knows the data well can go through the topics and figure out if it's a good representation, label a test set of the data and see how well it is divided into the clusters.

Figure 10: The most relevant word for the top 8 topics calculated. On the x-axis one finds the probability of that word.

When deeply studying the topics, it can be found that the clustering performs well but that multiple clusters are very similar to others, which could be adjusted by joining the similar ones for a result with fewer clusters.

Learning outcomes

For the NPP industry working to become more data-driven, it would be valuable to create domain-specific NLP models.

Research has been conducted on how BERT and similar language models can be used in domain-specific areas, as domain-specific language can be a major problem, like in the nuclear power plant industry or the clinical domain.

The lingo and jargon in the nuclear power plant industry differ between utilities as well as on an individual level. As the creators of the log posts come from a large range of operators over a longer period, the logs can differ greatly in language but have the same or similar meaning. This brings challenges to the NLP techniques.

To get the best performance from BERT for implementation in NPPs, BERT needs to be developed for domain-specific applications. To tackle this, domain-specific models and vocabularies could be beneficial to analyze the text data. This can be done in many ways, but a good way that doesn't require massive amounts of data is to continue pre-training of BERT from a checkpoint, using domain-adaptive pre-training.

Since there exist many documents at the Swedish NPP:s, such as error reports, to which one might apply domain-adaptive pre-training – it is possible. However, for such a solution, the model needs access to and be allowed to use the data for this purpose.

Conclusions

Operation logs from a Swedish NPP have been used for exploratory data analysis.

BERT has in this exploratory data analysis been used to find similar logs with semantic similarity search given a log, and also been used to find clusters in the data.

BERT could be used for many tasks in the Swedish NPP industry. Since the researcher is not considered an expert in the nuclear domain, difficulties in the proper evaluation of model performance exist. Still, examination of the results shows some trends in the data, which further can be used for the NPP industry.

The lingo and language in the nuclear power plant industry are rather special and differ from normal language as well as between different power plants which can pose a problem in the performance of the NLP models. Moreover, tuning an NLP model such as BERT by using domain-adaptive pre-training and creating a nuclear-specific vocabulary/tokenizer could be the solution to this problem.

7.3 AI TECHNOLOGY MATURENESS AND WHAT SOLUTIONS EXIST "OFF THE SHELF"

There exist many available solutions for AI applications. Some state-of-the-art solutions exist by using APIs, which given the limitations of the NPP industry is not applicable. Other state-of-the-art solutions exist as open-source or can be made available from commercial options. Furthermore, this section will focus on NLP solutions applicable to the NPP industry.

7.3.1 Open-Source Solutions

Within the fields of AI Engineering, Data Engineering, and Data Science – experts rely on open-source tools, packages, models, and programming languages for purposes from data exploration to AI implementations, OCR, and NLP models. To leverage these technologies, computation, and storage with best-practice, both knowledge of using the technologies and domain expertise are required.

Knowledge of how to use AI tools is required

AI offers powers new automatic ways of solving defined problems out of large amounts of data. More generally, AI uses models to make predictions from training data, where a model represents a mathematical relationship between elements of that data with the corresponding defined predictions. In the field of AI, framing or defining the problem as well as obtaining qualitative training data for that problem are the two most common tasks.

Understanding how to properly define the problem and how to make the data in a training-ready format require the expertise of the technologies with a minimum of consolidation of domain knowledge. Tools like Microsoft's PowerBI exists for assisting in better understanding the data and what can be answered with that data.

For a qualitative and robust model, there is a need for qualitative, quantitative, and representative data for what the model is to achieve. Gathering qualitative and quantitative amounts of training data for training is often sought to need ad-hoc development, since appropriate and representative training data for new use-cases in new domains and applications rarely exists and requires to be created.

At the point in the process when the AI application has a defined problem and training data exists in an appropriate format, a Data Scientist, Engineer, or AI expert can make informed choices of selecting models from open-source AI libraries or construct models using open-source tools. Examples are Keras, Tensorflow, and Scikit-Learn. When informed choices have been made, empirical testing and evaluation are used for model selection and adaptation.

> *There is a difference between the solutions and algorithms. How do you know which solution to use before you explore the data and use case? You cannot take an off-the-shelf solution. Nothing is today good enough, you have to verify your case and data. In terms of frameworks, there are many libraries in Python where bugs have been mitigated. Good enough to be tested, but you do not know before you test and assess for the specific use-case.*
>
> *– Data Scientist at AFRY*

Some techniques exist to make up for lacking quality and quantity of training data like data augmentation and transfer. In that process knowledge of the technologies is also required. Data augmentation is a technique used to increase the amount of training data given a sample, while transfer learning can be used to apply an already trained model that stores knowledge in new applications.

In terms of new applications or uses-cases of NLP in new domains, transfer learning becomes increasingly important since state-of-the-art models today are trained on vast amounts of data on super-computers. Some of the existing models exist as open-source available for the ones who have the know-how of how to use them, and can be referred to as pre-trained models for different applications or use-cases. Examples do exist applicable for the Nordic NPP industry.

Models that exist as open-source for the NPP industry and its associated main challenges

Some examples of specific transformer language models have been created for the nuclear domain, such as NUKEBERT [24], NukeLM [25], and NuclearN's language model (which the latter would not be open-source). These models have been trained for specific use-cases, like for categorization tasks, such as the example of CAP screening. As understood in the NPP domain, lingo and jargon vary on utility and individual levels which poses problems that have been discussed in Section 7.2.2 Moreover, the models are trained in the English language. This poses a potentially larger problem since translation from Swedish to English does not apply well for specific domain-specific words. One example where a state-of-the-art model has been trained on the Swedish Language was made by The National Library of Sweden (KB) introducing a new Swedish BERT model, called KB-BERT. This was seen as quite a leap from previous Swedish opportunities since earlier solutions used multilingual BERT. With KB-BERT, the Swedish use-cases today have the opportunities to use this large pre-trained model trained on Swedish training data, with ~3500 million words from news articles, social media, Swedish Wikipedia [26], etcetera.

Still, challenges exist with applying KB-BERT to new domains, applications, or use-cases. Within the clinical domain, there are similar challenges with applying NLP as exist in the nuclear power plant industry, as discussed by Lamproudis, Henriksson, and Dalianis [27]. Their research points out that using the standard pre-trained model is sub-optimal in specific domains like the clinical domain, as there exist large differences in language and vocabulary. They have developed a clinical language model for Swedish, the first of its kind, by continuing to train an existing Swedish generic language model, KB-BERT with in-domain data, hence, using domain-adaptive pre-training. It was trained on a large unlabeled corpus of 17.8 Gb uncompressed text from the clinical industry. The clinical BERT was then finetuned for 4 different downstream NLP tasks. The model significantly outperformed the generic model on all tasks apart from the general domain task, where performance was worse, indicating that the improvements in the clinical data performance were not only due to the large increase in pre-training data. Furthermore, Lamproudis, Henriksson, and Dalianis [27] could see an improvement in the performance after only training on 20% of the in-domain data. This work implies that there is a value in developing domain-specific language models.

7.3.2 Commercial AI Solutions

AI solutions

Many providers and alternatives to using the services exist. Today, it is possible to upload training data to any of the large cloud providers (like Microsoft Azure, Amazon Web Services, or Google Compute Engine) for them to automatically suggest use-cases, selection of models, and applications. Given the regulations of the Nordic NPP industry, this is not a viable use-case. It is also possible to order on-premise solutions, secure computation or storage, end-to-end implementations, etcetera. The different ways of using large as well as smaller providers are endless and depend on what is to be created, on requirements mapped to different technical trade-offs, and on the knowledge of the technologies which are to be used.

NLP solutions in the NPP domain

When it comes to commercial NLP solutions and applications in the NPP domain, NuclearN, Curtiss-Wright, and EPRI are at the forefront of the American NPP industry.

NuclearN has developed a platform within nuclear with several NLP solutions, such as automatic condition report coding, condition trend detection, safety reporting, and CAP Screening. The company is at the forefront of developing such a platform with state-of-the-art techniques. The founders have also won the Nuclear Energy Institute's 2020 Best of the Best Technology Innovative Practice award for Process Automation using ML. NuclearN's [28] models are custom-tailored for the nuclear domain. On their website they state:

> *"So when you tell a NuclearN predictive model "Declared feed injection pump B inop after trip on lowflow to SG2, entered LCO 5.4.5", Nuclearn's models know what you are talking about."*

NukelearN also states that it would not be viable for their solution to function as an off-the-shelf solutions. For it to function well for in a new language with other lingo and jargon, they would technically have to create everything from scratch and build it again.

Curtiss-Wright has implemented NLP on numerous tasks, such as classification of CAP entries as well as using NLP to compare documents to save time for regulatory inspections.

Moreover, both Curtiss-Wright and EPRI have worked on an industry-specific dictionary [13], trying to solve the challenges that specific domain languages pose for NLP.

7.4 POTENTIAL AI METHODOLOGIES AND DATA FLOWS

Given the implementation level and strategy, the methodologies and data flow of creating AI applications vary. The most central aspect of a potential application is the data which are to be exploited by AI models.

7.4.1 Methodology for AI Applications

Example methodologies will be listed in this section, based on the findings of this project. The methodology will differ, depending on the implementation level and strategy, as well as the technical use case.

Initial Methodology of Creating AI Applications

An initial PoC methodology example that can assist in gaining more trust in AI applications and attract new competence in the field of AI technology can be outlined in the following steps:

1. List potential resource consuming tasks for personnel suitable for an automatic workflow, which can run in parallel, and do not need current data of NPPs O&M.
2. Consult an expert within industrial AI applications, discuss the potential technical feasibility of making each task a potential AI technological use case, consolidate on regulatory and safety viability, and select a handful of use cases.
3. Hire master thesis students from the IT, data engineering, data science, or AI domain to investigate and set up a PoC.
4. Let them present their master thesis work to key personnel at the utilities.

Intermediate Demonstration of a Narrow NLP Application

Further, a narrow NLP application which can be shown to have a purpose and business value for stakeholders, can be outlined as follows:

1. Map out the data search routes of archived documents used in internal search functionalities, with metadata and authorization levels.
2. Let AI experts consolidate with novice users how their search experience can be improved. Ask questions such as "What is your most frequent search text?", "Can the search result improve?" or "How would you like to sort the results?".
3. Let the AI experts suggest new potential search functionalities together with an updated graphical user interface to adopt user feedback on the search results page.

4. Map out requirements and core needs with small iterations of graphical interface and consolidation with novice users of search functionalities.
5. Set up an offline and cloned dataset containing the data needed to demonstrate the technical viability of a set of searches.
6. Grant resources to develop and implement improved graphical interface search functionality on the created data set. Possible functionalities would include improved searches, recommendations of results and better suited searches, and feedback on the search results.
7. Test functionality and demonstrate the solution as well as recommended outcomes for implementation of such functionality in internal search systems for key personnel.

Demonstration of Online Anomaly Detection

Another example of an intermediate PoC methodology for AI applications could be an implementation of online anomaly detections in operation log posts which can be summarised as follows:

1. Grant resources, data access, computation, and storage at a utility for online anomaly detection.
2. Define what an anomaly is, given the current data that exists.
3. Define how the information of an anomaly is delivered to the key personnel.
4. Define how to technically update what is to be defined as an anomaly.
5. Define the system requirements.
6. Consult AI experts in putting the solution together using utility resources.
7. Test the solution.
8. Implement the solution.
9. Update and monitor the functionality.
10. Life cycle management.

7.4.2 Data Flow for AI Applications

Data flow for generic supervised AI applications consists of running data through a trained model for the prediction of results.

To properly train a model given a problem statement, training data need to be representative of the data that are to be used to make predictions. Training data can look very different, given the use case and problem formulation. If the training data lack in quality, the quality of the trained model will most likely also lack in quality. Furthermore, if the training data lack in quantity, most likely the model will be considered under- or overfitted, hence, giving the model bias.

When training data are collected and prepared, as well as models having been selected and implemented, the model will be exposed to make predictions of the data. Predictions are evaluated for performance indications and tuned for the model hyper-parameters. In short, an example of a workflow can be represented in Figure 11.

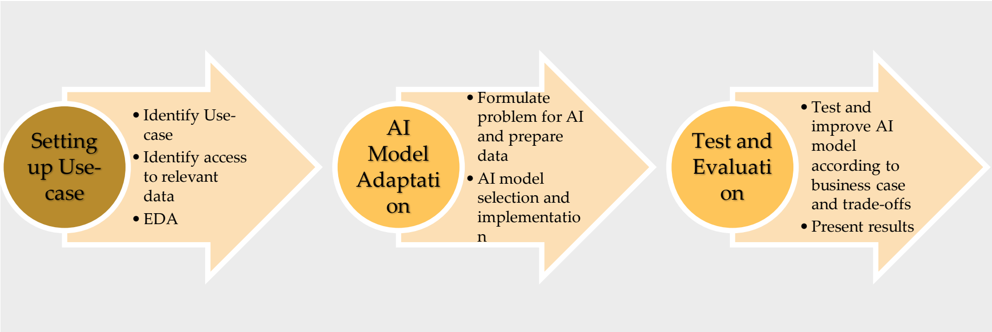

Figure 11: This figure represents how the process and data can transform during a use-case for initial PoC, or how the generic AI workflow could look like.

More detailed or advanced workflows for creating AI applications can be represented below, see Figure 12, where the exploratory data analysis process is elaborated.

Data sets are vastly different and in various formats, and in addition, they can contain noise or missing data, which need to be handled and managed. Furthermore, the data need to be prepared in accordance with various steps such as data processing and data wrangling, feature engineering and extraction, as well as feature scaling and selection. Data wrangling is a process that includes cleaning and transforming data, and whereas feature engineering is a way to extract features from data; with feature selection/scaling, features that are desired, are selected from several features for further usage. When a model is evaluated and tuned, the model can be considered inference ready for deployment.

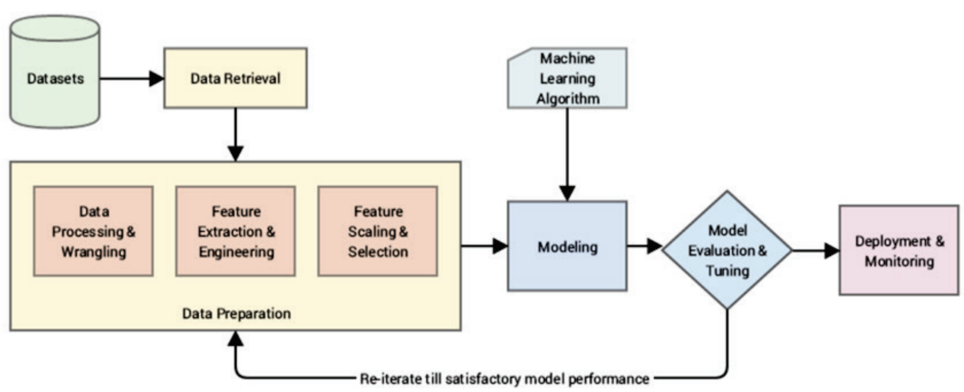

Figure 12: The figure shows what a standard ML workflow can look like. Notice the feedback loop for re-iteration until the model performance is satisfactory [29].

Implementing an inference ready AI model in the industry requires consideration pertaining to a proper infrastructure required to deliver results. Two approaches worth mentioning are Online Transaction Processing (OLTP) or Online Analytic Processing (OLAP), where the latter is more viable to elaborate on given the current nature of NPPs.

OLAP is a computation and storage approach of data and analysis, heavily used in many industries, with use cases that are not time critical such as business intelligence and reporting. Additionally, data are collected from a variety of sources and stored in data warehouses, then cleansed and organized into data cubes. Using OLAP techniques, models of analysis can make use of vast amounts and versions of data under one umbrella. OLAP is contrasted to OLTP and is traditionally being used to give answers to multi-dimensional analytics with swift querying and computing. NPPs can use this approach to create reporting and situational awareness by analyzing available data on isolated data sources, larger collections of data sources, different use cases from different points of views/processes/working groups or learn how to navigate through large amounts of data.

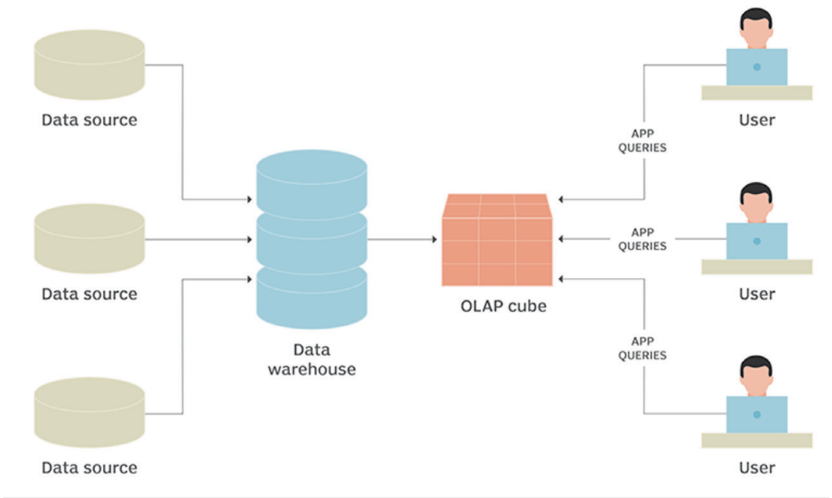

Figure 13: This figure is how one example of OLAP can look like on a high level, composed of entities and interfaces. Notice the OLAP cube, more explained in the text [30].

In OLAP, a sliced or "diced" multi-dimensional copy and a subset of the original data is created for analysis to be conducted on real data without disturbing the processes and integrity of the real data (see Figure 13). This way the original data is left undisturbed, but online analytical processes can still occur with close to real-time updates (given the update frequency of the OLAP cube).

8 Roadmap and Proposed Next Steps

8.1 FUTURE NEEDS OF AI TECHNOLOGY FOR NORDIC NPPS

The Nordic NPPs are suffering from an industry decline [31], resulting in difficulties in recruiting younger staff members. In this sense, AI applications, as close as possible to the main process may become a tool to recruit younger individuals. In the same context, but on the other end, it is hard to find competence with experience, the so-called experts. It is common for many seniors in the industry to work beyond retirement age, often because of interest but also because they are asked to by the staff remaining.

During the progression of this study, the Team has investigated opportunities to use AI, OCR, and NLP to support the NPP industry. Since the industry is documentation-heavy, such techniques can be used in many processes, such as project review processes, Safety Analysis Report (SAR) evaluations, and so on.

Within operations, the Project Team has evaluated process event data to find patterns that could predict the next event using text data and NLP. This type of application has not been found as very fruitful, and the Team concluded that to implement predictive maintenance algorithms, it is beneficial to read sensor data from the processes that are often seen too tough to be supervised by nuclear experts. However, such measurements often require Wi-Fi in the facility but the IT-security measures, and the cost and validation (jeopardizing) are reasons AI projects would be so complex, that there is a low likelihood of finding funds for execution.

The industry itself talks mainly about predictive maintenance and often points to the lack of Wi-Fi available measurements outside the strictest IT zones. Stepping away from the physical layers, a lacking maturity of being ready to adopt a more data-driven approach has been identified to be the greater challenge for the NPP industry in the Nordics to leverage AI, OCR, or NLP.

Improving the internal information retrieval is a central potential use-case for using the techniques in close future, to improve the situation and assist the work. Finding information efficiently seems to be a difficult task for other than experienced searchers and improvements are needed, as per mentioned by several interviewees. As the documentation of process control systems is extensive and resource-consuming, the already existing internal search functionalities can be further developed and presented in a better and more intuitive fashion. Advanced state-of-the-art AI-based search functionality can be integrated for supporting the engineers in finding better results from a search, suitable recommendations of results, suggest possible better-suited searches, and enable feedback loops for learning the search functionalities to be better for the next search.

Similarly, AI applications could be used in procurement support for faster evaluation of competing quotes. Submitted quotations are often at very different linguistic levels, whereby manual evaluation becomes very stressful and can be questioned from a qualitative perspective.

8.2 FUTURE INDUSTRY VISION

AI applications can be used as process support throughout mainly office applications as Expert Advisors, but also much closer to the main process itself. AI applications can make operations function resource-efficiently, and sustainable as well as make the NPP industry more competitive and safe.

There are many facets of the introduction of AI and the need for a proper and solid implementation strategy is evident. Introducing AI applications in the office environment would create more trust, awareness, acceptance, and knowledge of the technology itself. Using this, it will be easier to introduce the technology in applications closer to the main process, e.g. in measurement evaluations, such as vibration analysis and x-ray examinations.

At the far end of full-scale AI implementations, there are self-operated NPPs, nothing that will ever be implemented in the existing NPPs, but something that may be used when designing SMRs. One step on the way would be implementing a control room without the physical control room itself.

8.3 IDENTIFIED AND SUGGESTED INITIAL STEPS TO REACH THE VISION

In order to find opportunities for AI in nuclear power, it will be necessary to increase the awareness, understanding, potential use-cases, and trust of AI solutions and technology that can assist in finding the safest and most efficient use-cases and increase the chance of actual use of the technology integrated in any kind of process. There are misconceptions and skepticism among several employees in the industry, which must be overcome before any major advances can be made. To tackle this challenge, AFRY recommends introductory education of key personnel. Further recommended activities will be recommended in this section.

As there are IT restrictions at every NPP, to prevent malicious intent, access to data for analysis is just the first hurdle to overcome. Cloud based services has historically not been available for use, but the possibilities of using these services has recently changed.

Finding business cases and showing concrete value with small PoCs can assist in gaining more trust and awareness as well as seeing opportunities for AI applications.

Finding strategies for AI-introduction, AFRY recommends increased collaboration with international actors, i.e., EPRI which is the equivalent actor to Energiforsk in the US, and an actor investigating several areas with a data-driven perspective.

AI is good for automizing manual tasks. Currently, AI technology is mature to assist in narrow applications. AFRY recommends employees list their most manual and repetitive tasks that are estimated to require an unnecessarily large amount of resources.

AFRY also recommends listing, choosing (dependent on feasibility and viability), developing, and running several demonstrations or proof-of-concept projects off-line or in parallel while preparing the strategies. These projects could aim to inform workers and will not be able to take decisions – to investigate potential use-cases and incrementally gain trust as well as awareness of potential applications.

One example use-case and project could be to let AI scan regulation documents and map towards inspection procedures for detecting discrepancies. Another example use-case and project could be to automize the way employees find and fix problems at NPPs since this could be a very resource-consuming task.

AFRY recommends allocating more resources for Data Engineering/Science and IT (Information Technology) competence.

Further elaborating what the future needs are for enabling AI technology in the Nordic NPP industry to be able or ready to adopt AI technology, what is most immediately needed are

- added competence, and/or consolidation of experts in the following fields:
  - × Change Management
  - × Data-Driven Operations and Maintenance
  - × AI, Automatic Data Analysis, Data Engineering and Science, and Cloud Computing
- increased understanding, acceptance, awareness, experience, and trust in the technology, by activities such as:
  - × Education of key personnel
  - × Developing small and narrow applications
  - × Mapping out how data-driven solutions can get easier access to read data

8.3.1 Content from AFRY Data-Driven Maintenance

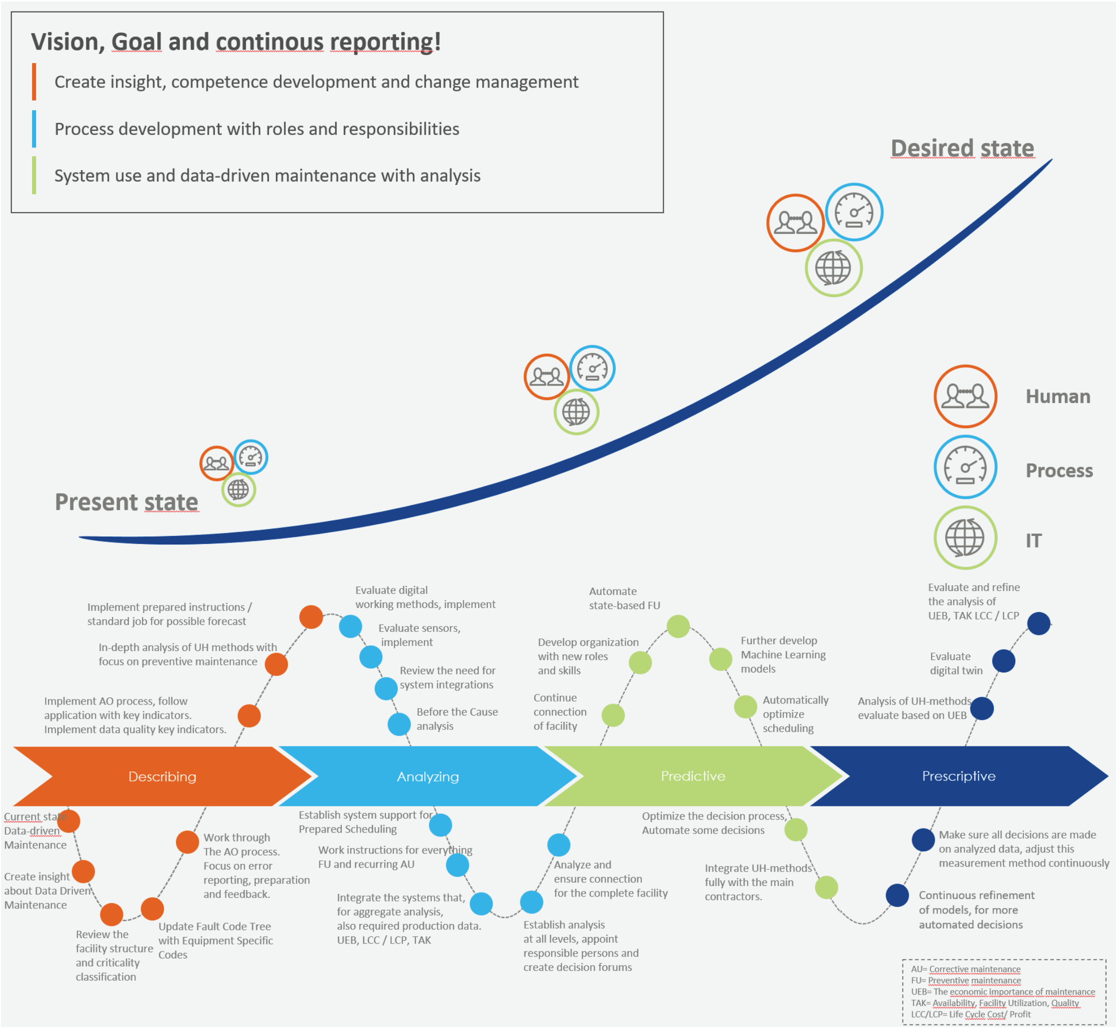

Figure 14: Image from Trivalo, proposing a general methodology in order to become more data-driven. The bullets listed in originate from Trivalo, an organization today integrated with AFRY.

Often, it can be observed that industry organizations that wish to adopt new technologies meet the requirements of trendy buzzwords, but unwillingness or reluctance to change daily work or processes. Trust for adopting modern technology is low, although the core industry competence itself is high. To be able to adopt a more data-driven approach, it is important to education, change management, consistent feedback, and continued maintenance of the data-driven systems, see Figure 14.

Data-driven O&M is a tool for being increasingly competitive in industrial markets. At the same time, in many cases, it can, by humans, be seen as a threat of being replaced by machines. Humans have difficulties retrieving information in too large quantities, numbers of sources, and time intervals of data – that is where machines can assist with data-driven information retrieval.

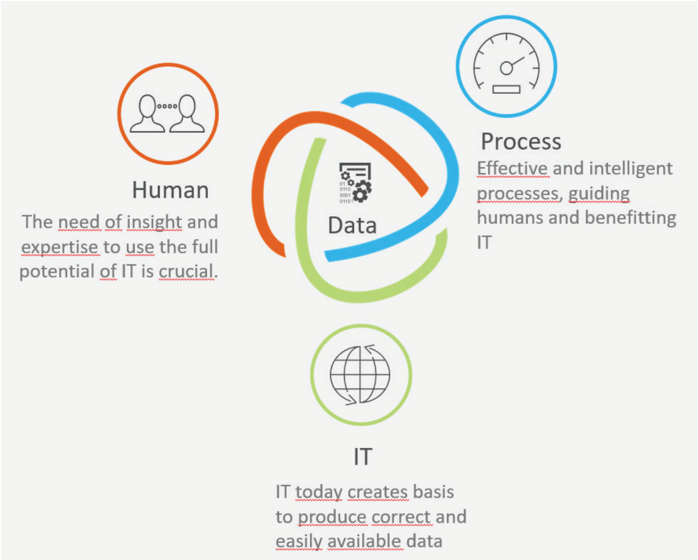

Figure 15: Thorough investigations from three different subjects are required to define the current state – subjects are composed of humans, processes, and IT.

Initiatives in industries with educational workshops and consultations have been beneficial and efficient for increasing trust and decreasing the reluctance for using and aiding in using the results of automatic data retrieval of modern data-driven techniques. There often exists a strong culture where groups of employees make decisions based on previous experiences, but still do not trust the information that automatic data-driven information retrieval finds. To succeed with data-driven maintenance, it is important to:

- Clearly define where the current state of an actor is in terms of data-driven matureness. With examinations from three different subjects, humans, IT, and process, the balance is important (see Figure 15). Typically, if too much focus is on IT, the imbalance leads to unsuccessful solutions, where humans and processes do not align with the solutions implemented. Rarely the answers are coherent within an organization. Therefore, there is a need for a thorough investigation of the status.
- Define a three-year goal for where the organization shall be in three years in regards to the data-driven maintenance matureness status. When starting work with data-driven maintenance, technical challenges are often in the form of lacking data quality. Therefore there is a need to early on understand the matureness and plan for the data to be more qualitative before initializing the work.
- Have a roadmap with activities necessary to be identified in terms of increasing the data-driven maintenance. Organizations need to be assessed, studied, and investigated where they are at the start of work. In addition, what level of maturity needs to be specified. To some extent, the highest level of maturity and ubiquitous data-driven solutions can be costly and unnecessary. The possible solutions are recommended to be classified depending on how critical and value-adding they are.

- Find the "low-hanging fruits". A potential low-hanging fruit for becoming more matured data-driven is to aim for having more qualitative data and employ a more qualitative way of data creation. Naturally, documentation in a free-text format is often without documentation instructions, which leads to more difficult interpretations by machines. Automation leading to a small increase in efficiency can lead to large savings for large actors. Finding use-cases, developing proofs-of-concept, showing the gains, and incorporating continuous feedback has worked in industry cases for gaining trust and matureness of the technology. More "low hanging fruits" can be found in section 8.3. and 4.2.

8.4 IDENTIFIED CHALLENGES TO REACH THE VISION

The bullets following in this section compile a brief description of the challenges the nuclear industry faces, facing AI-introduction in their processes.

- Collaboration across the industry

  There is today no existing center of expertise or separate organization to enable AI-introduction in the nuclear industry. Collaboration between utilities, actors, and countries for data-driven research and development seems challenging but would to a large extent facilitate the industry.

- The complexity of the NPPs

  NPPs are large facilities and to a large extent wired with physical cabling and no network. Introducing more sensors to provide better data quality is not only complex work but also costly.

  Due to the complexity of NPPs, planning is complex too and as a consequence, planning an AI implementation may be inaccurate or lack in quality.

- Competence in the relevant fields

  The general awareness of AI is low.

  The general trust in AI is low.

  General IT competence and knowledge are limited.

  Engineers want to trust the results of AI models, but to gain the trust there is need to use the outputs of the models, which has been found to be difficult.

  > *"It's still quite a concern for our industry of engineers who wants to know exactly how something works and exactly what the outcome is based upon before approving the result."*
  >
  > *Interviewee from Curtiss-Wright*

- Security Regulations imply limited opportunities to adopt new tools. Historically, the security of the NPPs limits the opportunity for using wireless communication. However, possibilities to use Wi-Fi at NPPs has recently become available.

  The security of the NPPs has previously excluded the opportunity for using cloud services, meaning that there were no alternatives regarding solutions or tools for computation and storage of data, other than using on-premise solutions disconnected from the internet. However, the possibilities of using cloud services has recently become more available. The NPPs in the forefront of implementing Wi-Fi and cloud services will break important ground for other nuclear actors.

- NLP obstacles

  Even utilities that operate under the same legislation still use language/phrasing/wording/dialects/jargon that varies between workers, sites, utilities, actors, (and countries), which makes NLP implementations harder.

  The NLP models that are considered State-of-the-Art are based on the English language and Nordic-based NLP models are sparse. The existing Nordic language models are not performing as well as the English ones since they are not trained on the same quantitative or qualitative data.

  The language used at single utilities varies between local language and English, which to a certain extent limits the number of documents an NLP function can train on.

8.5 REPORTING ON THE GAP BETWEEN THE NORDIC NPPS' CURRENT SITUATION AND THEIR VISION

There is a need for the Nordic NPPs to implement a strategic plan to step into the AI future in a controlled manner. Such strategies must be made in a well-structured manner. If not, the introductions would likely fail at first implementation.

In a way, the utilities that set up a strategy for their AI implementations will define their gaps, as more or less all utilities start from zero.

This gap is likely more a result of scarcity of new technology (especially software technology), rather than a lack of interest and understanding of future useability.

8.6 FORMULATION OF INITIATIVES AND STRATEGIES THAT NEEDS TO BE IN PLACE FOR THE DIFFERENT STEPS IN THE EVOLUTION PATH

Not only is it necessary for any NPP to implement a proper strategy for the AI implementation. It is just as necessary to identify the specific areas that are feasible to carry out the implementations.

A curious fact is, however, that AI functions have already been implemented in all nuclear facilities. This has likely not been known to the utilities. It must be assumed that the introduction has been made in a "black-box" installation, with a focus on the function.

This inadvertently leads to the conclusion that, if the AI function is contained inside one "box" with well-defined inputs and outputs, the complete function is easier accepted.

8.7 EVOLUTION ROADMAP TO CLOSE THE GAP

In this section, a brief roadmap to set up a strategy for AI implementation within a utility is provided. The utility is used before NPP to widen the scope possible.

In the AI strategy, it is vital to identify the technical and non-technical areas suitable for AI implementation. It is essential to identify areas of quality improvement, technical assistance in decision making, areas where process connections are necessary for full AI implementation, where cost-efficiency can be improved, where staffing is under-established or deteriorating, etc.

Suggestions for technical areas applicable for AI-function implementation:

- OCR as support to operators reading indications from video screens. AI functions can prevent the progress of operations if differences are detected.
- Behavioral deviation functions can be used to detect deviations between work permits released and actual actions taken inside the plant according to the permit, e.g. wrong area accessed, etc. Such function may even limit the risk of radiation exposure in case an employee enters the wrong area (even if that should be locked).
- Analyzing measurements such as X-ray, ultrasonic, and eddy current can be supported by AI-analysis tools. Studies have shown that lung x-rays can be verified up to 96 % accurately by AI, but only 77 % by doctors.
- Pattern recognition can be used to separate between known objects and unknown objects. Such functions can be used in the security check entering the facilities.
- Facial recognition software can be used in several applications. A direct warning in case of unauthorized faces recognized in highly sensitive areas.
- Mood recognition software can be used before sending staff members to e.g. stressful tasks, avoiding sending people non-conditioned for specific tasks.

Suggestions for non-technical areas applicable for AI-function implementation:

- NLP (Natural Language Processing) is used as Expert Advisors to reduce the senior expert workload. NLP can find the essentials in reports much faster than any expert, hence providing the expert with an improved "search tool".
- This kind of NLP function can also be used by introducing younger employees into the expert field, hence securing a generation shift.
- Analysis using AI of information available externally. This type of analysis would make up an example of how an organization can use openly accessible information to create information that was never intended for publication.

In all cases, it is vital to identify which process objects or databases must be accessible for each AI implementation, and this may be the tricky part as a full-scale AI implementation means AI functions must interact with process signals.

To provide a vision for implementation such as described above, a use case study was made of the encapsulation process at SKB's future encapsulation plant in Oskarshamn. The study, which is based upon a couple of videos on YouTube, is presented in appendix C. An interesting use of AI, would be to analyze the two videos that the presentation in made upon with AI to find information that SKB never intended to release, just as mentioned in the sixth bullet above.

Of course, any strategy for AI implementation must consider Regulatory aspects. As this subject stands today, IT protection and the use of software in the process are regulated and must be considered in the strategy.

9 Ensuring Governed Technology and Accounting of Main Risks

9.1 REPORTING ON SUGGESTIONS FOR HOW TRANSPARENCY AND GOVERNANCE OF TECHNOLOGIES CAN BE ENSURED

It is becoming increasingly apparent that AI does not just scale solutions - it also scales risk. In this context, data ethics and AI ethics are business imperatives rather than academic subjects. To comply with the ethical dilemmas this new technology presents, companies need a clear plan. To operationalize data and AI ethics, they should develop and improve an industry-specific ethical risk framework for data and AI, see Figure 16, which should majorly contain the following six steps:

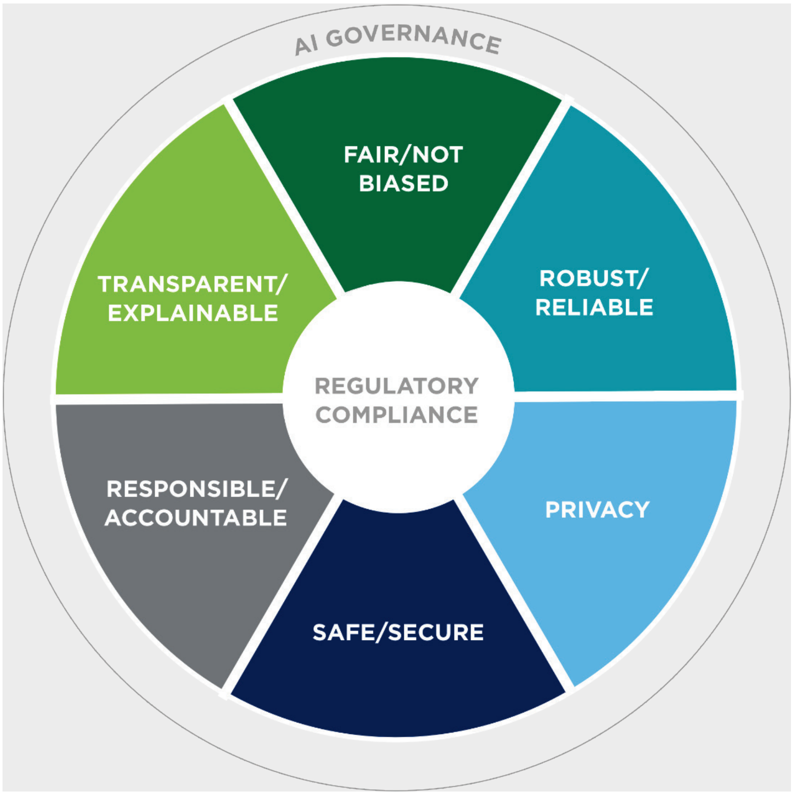

Figure 16: Steps for an ethical risk framework for data and AI.

A. Fair and Unbiased

To ensure that AI applications are equitable across all participants, internal and external checks must be made. It is one of the most discussed issues around AI to ensure that data and algorithms minimize the consequences of discriminatory bias and avoid the pitfalls introduced by humans during the coding process. It also protects those receiving AI-driven decisions from unintended, unfair consequences.

B. Transparency and Explainability

Organizations need to ensure that algorithms, attributes, and correlations are open to inspection so that project participants can comprehend how their data is used and how decisions are made. Moreover, ML is becoming increasingly complex, in addition to deep learning neural networks, which behave like black boxes without an explanation of how they determine results.

C. Responsibility And Accountability

When AI outputs do not meet expectations, policies must be in place to determine who is responsible. This issue is a prime example of the uncharted waters of AI.

D. Safety and Security

To ensure that AI systems are safe from cybersecurity risks that can cause physical or digital harm to consumers, sufficient measures must be put in place.

E. Privacy

The privacy of data should always be respected, the data should not be used beyond the stated purpose and the moderator should always opt-in and out of sharing the data.

To implement these bigger objectives in the framework we need to:

1. Assess existing infrastructure that a data and AI ethics program could take advantage of;
2. Employ the lessons of the NPP to change how you approach ethical issues;
3. Improve product management training and tools;
4. Promote organizational awareness;
5. Provide employees with formal and informal incentives to take part in identifying ethical risks related to AI; and
6. Assess impact and engage stakeholders.

9.2 RISKS, CHALLENGES AND LIMITATIONS FROM THE INITIATIVES

9.2.1 Legal and regulatory demands

From a regulatory perspective, there are no direct requirements for AI. However, the regulators are very restrictive when it comes to software-based systems, especially in implementations close to the reactor or reactor control areas and functions.

During retrofit projects over the past 20 or 30 years, process control installations have increased in use, but no AI functions have been implemented yet.

There have been a few projects on the vendor side, starting with fuzzy logic in the 90s but nothing has yet reached the market, except Excelon’s predictive maintenance function.

Introducing AI applications in NPPs must follow thorough legal regulation updates, to define the jurisdiction. E.g. if an (AI-based) Expert Advisor suggests approval of a measurement result, the operator accepts the EA and the measurement is later found faulty; where is the fault made? (aka who is to blame)

9.2.2 Security demands

There are three rather than one items to discuss, Cyber security, physical protection, and Information security

Cyber security

The area of cyber security is one of the high restrictions. Thus it has been difficult to find individuals willing to be interviewed. Hence this area has been written based on the personal experience of some of the project team members.

The IT structure implemented at the Nordic NPPs is set on several levels. The closer an application comes to the nuclear process, the higher the degree of the security class.

Passing information from one security class to another is restricted with the use of devices such as gateways and data diodes, strictly determining what data can be sent to which server in the network.

Although IT security itself contains a lot of software engineering, there are no evident AI-use cases presented. Detecting IT intrusion attempts is possibly the only technical field in which AI applications can be useful, predicting attempts to breach security. No work is ongoing in this area.

Albeit IT security is designed to restrict information flow between security classes, it does not in itself prevent the use of AI applications within one security class. Neither will the IT security prevent the information flow from an AI implementation to a lower security class as long as the information follows set rules and principles.

Physical Protection

The subject of physical protection is just as restricted as cyber security. Hence this area has also been written based on the personal experience of some of the project team members.

The physical protection structure implemented at the Nordic NPPs is, just like the cyber security, set on several levels. The first of these levels can even be seen visually from outside the NPPs. The closer an individual comes to the nuclear process, the higher the degree of protection class.

Interestingly, there are already AI applications implemented in physical protection. If these implementations have been made oblivious of the AI-application content or not is unknown.

In the area of physical protection, there exist several AI applications that can easily be implemented. Face recognition software can be implemented and used to automatically investigate intrusion alarms using drone in office applications. Similarly, drones can be used to investigate foreign objects between the outdoor fences or use face recognition software to identify people in the same area.

As the NPPs are no-flight zones, the drones used by security can even be used to disable foreign drones.

Information security

In the same way that AI functions can be used in cybersecurity to identify unwanted behaviors, a related function could be to study human behavior. Such a function could find deviations from expected behavior, combining documented activities (e.g. pre-job briefings, user manuals, etc.) with human behaviors from different sources (entry/login, movement patterns, etc.).

Another difficult area in information security is the aggregation/accumulation of available information, where many small insensitive pieces of information can be combined into something that becomes sensitive. AI could support that kind of analysis, and indirectly also become an offensive tool for attackers. It could also be combined with knowledge about which people have access to what information and/or in which places/zones the information should be available.

Classifying the result from an AI function from an information security perspective is a challenge when it is hard to understand what information has been used to come up with the conclusions made. Despite classification being a challenge, it could also become an opportunity; If an AI function with access to very sensitive information, uses it to analyze documents or behaviors from less restrictive contexts, it could point out deviations. For example, an AI function could use Dimensioning Threat Description to find incorrect assumptions in less sensitive texts. This could clarify the necessity to restrict sensitive information to fewer staff members.

9.2.3 Technical limitations

Technically speaking, the lack of Wi-Fi measurements and IT-security measures challenges the AI-application introduction. Computation and storage of data is required to be executed on premise. Inability to share data between companies brings limitation. In many older facilities, there are also space restrictions, preventing physical hardware from finding a footprint inside controlled areas. Even so; Please allow us to talk about opportunities instead.

10 Summary & Conclusions

10.1 SUMMARY

This report gives an overview, analysis, recommendations, findings, and conclusions on the topics of suitable AI applications for Nordic NPPs and the conducted feasibility study on AI technologies in nuclear applications. The focus is wide while also narrowing down on identifying "low hanging fruits" from a nuclear perspective. Applications of focus have been on digitizing documentation and assisting operation-, technical- and maintenance staff in making informed decisions.

The introduction of the report aims to give readers an understanding of the subjects and execution of the project. The basis for the report is several interviews with nuclear utilities, institutes, and suppliers, trying to find the areas of interest to introduce AI in the NPP industry - where the focus has been to collect opinions and ideas from different nuclear utilities, institutes, and suppliers concerning challenges and opportunities that makes it possible to introduce AI applications in nuclear applications. Investigations and materials for analysis have been executed with a wide focus area while also being focused on narrow or more in-depth applications.

Furthermore, technologies and solutions of high potential from other industries than the Nordic NPP industry have been surveyed, collected, and presented. Following the survey, an opportunity analysis with experiments, discussion on the challenges, and presentation of the "off-the-shelves" AI solutions and tools for the NPP industry are presented.

Proposed future steps and associated identified challenges show many interesting results. For the Nordic NPPs to be able to adopt data-driven or AI applications solutions, recommendations have been laid out and "low-hanging fruits" have been identified.

In the closing sections of the report, reporting on ensuring governed technology and accounting for the main risks are presented.

10.2 SUBJECT CONCLUSIONS

The main conclusion from interviewing Nordic NPPs is that there is an underlying scepticism against using software in the NPP industry, and AI applications are no exception.

Interviewees have provided AFRY with use-cases of high potential and assisted in finding challenges as well as opportunities for implementing AI solutions in the industry. Interest for OCR applications is generally low, while mentioned potential applications exploiting data with NLP are numerous.

The industry often points to the lack of Wi-Fi available measurements inside the strictest IT zones. Although, when stepping away from the physical layers, a lacking maturity in being ready to adopt a more data-driven approach has been identified to be the greater challenge for the NPP industry in the Nordics to leverage AI, OCR, or NLP.

Opportunity analyses have shown that there exist a multitude of applications and use-cases among the existing technologies, products, and solutions that can be useful for the NPP industry. To ensure governance, safety, and efficiency, the solutions or applications need to be designed, modelled, developed, and tested for the respective use-case, or domain. Based on the implementation level and strategy of such application and the use-case, the methodology and data flow will differ.

Challenges exist in implementing AI solutions, such as that trust and awareness of the technologies are low. Increasing the knowledge as well as safe development of narrow applications can benefit initiatives in the domain. One example of a recommendation is to find business cases and show concrete value with small PoCs, to gain more awareness and trust for possible applications. Such a business case could be to improve the internal information retrieval which will assist in improving the situation for especially novice workers in finding information more efficiently.

Results show that AI with applications such as OCR and NLP can in any way assist in digitizing, analyzing, and efficiently managing information and that the applications can together with modern tools, combined with cyber security solutions, have the potential to be very beneficial for the Nordic NPPs.

10.3 PROJECT CONCLUSION

The project has run well.

The start-up meeting (2022-01-28), served well in fully understanding the orientation, content, limitation, scope, etcetera of the project. An outline was also proposed in the report.

The first part of the project consisted mainly of conducting interviews with this project's reference group. The interviews provided many useful insights and further relevant interviewees.

Having a wide area focus, while narrowing down on identifying "low-hanging fruits" from a nuclear perspective have provided some challenges for the project team. In order to the associated challenges, the method of the interviews have been successful.

Although the reference group availability has varied, the primary sources of interviewees have enabled analysis and further information retrieval, and outreach to other relevant actors in the same as well as other industries.

The mid-way meeting (2022-04-05), reported on the project's status and direction. Particular topics, relevant intermediate results, and matters deserving extra focus were discussed.

The vast material collected resulted in enabling analysis with both wide and narrow scopes and technical experimentation, which has resulted in a qualitative delivery of the project.

The results have been compiled in this report with results proposing next steps, "low-hanging fruits" for the NPP industry and focus areas of future suggested development. A summary of the recommendations is stated in the following section.

At the final presentation (2022-06-29), AFRY presented the results of the projects and delivered the report, the PowerPoint as well as the executive summary in PowerPoint format.

10.4 RECOMMENDATIONS

AFRY recommends:

- To increase initiatives, educational AI can increase trust and decrease the reluctance for using the technology. This has shown to be efficient in other NPP industries.
- Clearly define, through thorough investigation, the current state of the utilities in terms of data-driven matureness. This should be done from three different subjects - humans, IT, and processes.
- Define a three-year goal, for where the organization shall be in three years in regards to the data-driven maintenance matureness status.
- Have a strategy with activities necessary to be identified in terms of increasing the data-driven maintenance.
- Increase the general awareness, understanding, potential use-cases, and trust in AI solutions and technology. To tackle this challenge, AFRY recommends the introductory education of key personnel.
- To list, select and develop small business cases and show concrete value with small PoC. This can assist in gaining more trust and awareness as well as seeing opportunities for AI applications. AFRY recommends employees list their most manual and repetitive tasks that are estimated to require an unnecessarily large amount of resources.
- To establish an increased collaboration with international actors, such as EPRI or IFE, and an actor investigating several areas with a data-driven perspective.
- To allocate more resources for Data Engineering/Science and IT competence, one reason is that the use of existing solutions and tools for the technology in a new domain or use-case requires knowledge.
- To allocate more resources for consulting on Change Management within IT and Data-Driven Operations and Maintenance, one reason is that a transition requires the definition of where the current state of an actor is in terms of data-driven matureness and that the definition rarely are coherent within an organization.
- To map out how data-driven solutions can get easier access to necessary data

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Appendix A: Method of Conducting the Interviews

The criteria for reaching information saturation[1] are difficult to define in advance but will be assessed by experts in AI and by evaluation of the scope of the study.

Given the scope of the study, the budget, and the timeline of the study, the selection of interviewee samples needs to be created and reached efficiently from the primary data sources/interviewees. Risk can be mitigated by ensuring collaboration with primary data sources/interviewees early in the project.

The project set-up or process of gathering knowledge will in this section be further described.

PRIMARY DATA SOURCES/INTERVIEWEES AND POPULATION

The primary data sources/interviewees[2] consist of this project's steering committee and AFRY employees with experience in the power plant industry.

The population of the study is large but can be further limited by an increased focus on applications associated with text data applications. The identified population[3] are identified as follows (with selection for ideal interviewee/-s with*):

- Text data analysis
  - × People in the Nordic power plant industry working with text data analysis*
  - × People in the power plant industry working with text data analysis*
  - × People in the energy industry working with text data analysis
  - × People in other industries working with text data analysis
- AI strategies of the Nordic power plant industry
  - × People in the Nordic power plant industry working with strategies for text data analysis*
  - × People in the Nordic power plant industry working with strategies for data analysis
  - × People in the Nordic power plant industry working with digitalization strategies

[1] *Information saturation* can be defined as the point at which the data collection process no longer offers any new or relevant data or when gathering fresh data no longer sparks new insights. The concept of saturation is important when determining the sample size of interviewees and making decisions in qualitative research.

[2] *Primary data sources/interviewees* can be defined as the known resources for information prior to interviews or study initialization.

[3] A *population* can be defined as the possible participants on which the study can applicably be based on.

SELECTION OF INTERVIEW SAMPLES

In order to gather the interviewee sample[4], a non-probabilistic sampling technique[5] was chosen, with the use of chain-referral sampling[6]. This method brings sampling bias from the sampled interviewees but is effective since it allows faster localization of applicable interviewee samples. For reducing sampling bias, maintaining confidentiality, and increase the validity of research findings, the sampling was made in accordance with these steps:

1. Create a definition of the population
2. Consider the sample size
3. Select and assess the settings of the referral method
4. Gain access to primary data sources/interviewees
5. Initialize the chains and identify the following potential interview subjects
6. Pace and monitor the chain-referral process
7. Discontinue the chain of referral

INTERVIEWS

Since the aim of the interviews is an in-depth investigation of several aspects of the Nordic NPP industry, and to which there is a degree of uncertainty previous to the interviews, as well as to explore the thematics and nuance in a highly technical industry with interviewers being experts of the techniques which are studied – a semi-structured interview[7] format has been defined as the most suitable, and as the primary source of data for information retrieval.

Most interviews were conducted virtually either via Microsoft Teams or other tools, recorded, and transcribed with speech-to-text to facilitate coding the interviews, i.e., finding recurrent themes and patterns, further delineated next in this section. The recordings were treated according to GDPR regulations. Furthermore, established interview techniques were used to minimize contamination of data[8], with the questions being sorted according to themes.

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[4] The *interviewee sample* can be defined as the selection of people that are aimed to interview for the study.

[5] Non-probability sampling is a sampling technique in which the researcher selects samples of interviewees based on the researchers' judgments rather than random selection, meaning that this sampling method depends heavily on the expertise of the researchers. The technique is carried out by observation, and researchers use it widely for in-depth qualitative research.

[6] When primary data sources/interviewees exist, desired sample characteristics are rare to find, and the applicable sampling population is unknown – the type of non-probabilistic sampling technique called *chain-referral sampling* method can be useful. The method is a popular business study method that is based on interviewees' referrals or nominations to recruit further appropriate interviewees samples. By an introductory collection of information from the primary data source/interviewee together with inquiries on referrals or nominations of further interviewee samples, it is possible to find references to gather more data efficiently.

[7] Questions are then asked as open-ended questions and are to be interpreted by the interviewer for information retrieval. Semi-structured interviews are largely used in qualitative research and can result in producing rich and observational data. Applying a semi-structured interview methodology differs from structured interviews, which in constrast have a rigorous set of questions that do not allow interviews to divert.

[8] The semi-structured interview methodology requires preparation for selections of interviewee samples and interviews, pre-requisite knowledge in the field of what is researched, trust and confidentiality

Compiling information

Data were compiled into information[9] by using the specifications of the study, as the perspective or lens when going through the reviewing notes, transcripts, and/or recordings from the interview, which successfully filtered out irrelevant data for the study.

between the interviewee and interviewer, as well as guidelines for the interviewer for mitigating *contamination of data* that emerge from the interviews.

[9] Compiling the information can be described as assigning wordings, phrases, sentences, or paragraphs into labels of interpreted meaning. This allows producing logical schematics or maps, organizing of information, clustering of different thematics or key issues in the data, etcetera.

Appendix B: Thesis Report

http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-479344

Appendix C: Rome Presentation

In this appendix a presentation is provided. The presentation is one of AFRY's contribution to EPRI's "AI and Electric Power Summit" in Rome, Italy on October 4-6, 2022.

See https://www.aielectricpower.com/

The presentation is provided as a pdf-file. The name of the file is **Tracking spent fuel – presentation.pdf**

Appendix D: Topic analysis

Topic analysis is an NLP technique that automatically assigns topics to text data. Topic analysis is often used to analyse unstructured text, including emails and social media interactions, then process and sort this information, helping businesses to discover the topics their counterparts mentioned most often in relation to their product, brand, or service.

The vast amount of data that businesses receive today is unstructured, and manually sorting it is not effective. By using NPL techniques, like topic analysis, businesses can sift fast through large amounts of data and pinpoint the most frequent topics used.

The project team decided to use Topic analysis during the evaluation of AI used in three energy groups, Power grid, Wing and Hydro. This analysis was made using Google Colab.

Each group was analysed, automatically producing the sentences with highest intensity based on its text material, which were included in this report. A Word Cloud based upon the 100 most frequently used words, was also made but omitted in this report.

Using Topic analysis, it would be possible to compare similarities and differences between different groups. This however made little sense to this report for Power grids, Wind and Hydro Power.

For more information on Topic analysis, please visit
https://monkeylearn.com/topic-analysis/

FEASIBILITY STUDY ON ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN NUCLEAR APPLICATIONS

This report gives an overview of the opportunities and challenges nuclear Utilities face in implementing AI-based functions in their everyday business. The basis for the report is several interviews made with various Utilities, Institutes, and suppliers.

The main conclusions are, that AI functions represent a virgin territory but it is easy to find useful and realistic implementations, which have been exemplified in this report.

Energiforsk is the Swedish Energy Research Centre – an industrially owned body dedicated to meeting the common energy challenges faced by industries, authorities and society. Our vision is to be hub of Swedish energy research and our mission is to make the world of energy smarter!

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