Birgit Salomonsen Øygard

Data Models and Data Utilisation for Improved Diagnostics for Gas Detectors

Master's thesis in Cybernetics and Robotics
Supervisor: Mary Ann Lundteigen
Co-supervisor: Arvid Bjarne Nilsen, Eirik Halvdan Sølvberg Bratbak
June 2023

Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Engineering Cybernetics

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Norwegian University of
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AkerBP

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Abstract

Gas detection plays a critical role in offshore facility safety, but adverse weather conditions can affect infrared radiation (IR) line gas detectors. These detectors rely on IR beams to detect gas concentrations, and when weather conditions obstruct the path of the light, or condensation forms on the lens, it can lead to detectors that have dirty optics or are beam blocked. The current practice of corrective maintenance lacks efficiency in resource management.

The purpose of the master thesis is to develop a data model for monitoring optical gas detectors, specifically in the context of Aker BP. The goal is to improve maintenance planning by integrating data from gas and weather detectors. By analysing historical data and correlating it with weather conditions, the data model aims to identify potential issues before they lead to equipment failure and enable proactive maintenance measures. The data model is implemented in Cognite Data Fusion (CDF), a platform for integrating information technology (IT) and operational technology (OT) systems.

The thesis specifies the problem space related to weather conditions causing dirty optics and beam block in optical gas detectors and proposes a solution space involving the implementation of a data model that visualises patterns between failures in gas detectors and weather conditions. The data model aims to enable more efficient maintenance planning, avoidance of failures, and identification of susceptible detectors.

The design of the data model encompasses the entities gas detectors, platforms, facilities, weather factors, object types, catalog profiles, function blocks, and notifications, with associated attributes. The source systems used in the thesis include the Aveva Net and Systems, Applications, and Products in Data Processing (SAP) for storing and managing asset information and maintenance data and safety and automation system (SAS) for gas detector events. CDF facilitates the integration and linkage of data from different sources and data from all of the mentioned sources are already provided in CDF data sets.

The data model is implemented in CDF, but challenges were encountered in populating the data model. Further work is suggested, including the integration of the gas detector diagnostic alarms and events, notifications, and weather data to the data model and utilising it for predictive maintenance and analysis of the relationship between gas detectors and weather conditions.

Sammendrag

Gassdeteksjon spiller en avgjørende rolle for sikkerheten på offshore-anlegg, men ugunstige værforhold kan påvirke infrarød stråling (IR)-gassdetektorer. Disse detektorene er avhengige av IR-stråler for å detektere gass, og når værforholdene hindrer lysbanen eller det dannes kondens på linsen, kan det føre til at detektorene får skitten linse eller blir blokkert. Den nåværende praksisen med korrigerende vedlikehold mangler er lite ressurseffektiv.

Formålet med masteroppgaven er å utvikle en datamodell for overvåking av optiske gassdetektorer, spesielt i sammenheng med Aker BP. Målet er å forbedre vedlikeholdsplanleggingen ved å integrere data fra gass- og vær-detektorer. Ved å analysere historiske data og korrelere dem med værforhold, har datamodellen som mål å identifisere potensielle problemer før de fører til utstyrssvikt og muliggjøre proaktive vedlikeholdstiltak. Datamodellen er implementert i Cognite Data Fusion (CDF), en plattform for integrering av data fra informasjonsteknologi (IT) og operasjonell teknologi (OT)-systemer.

Oppgaven spesifiserer problemområdet knyttet til værforhold som forårsaker skitten optikk og blokkering av stråling i optiske gassdetektorer og foreslår en løsningsmodell som innebærer implementering av en datamodell som visualiserer mønstre mellom feil i gassdetektorer og værforhold. Datamodellen har som mål å muliggjøre mer effektiv vedlikeholdsplanlegging, unngåelse av feil og identifisering av sårbare detektorer.

Designet av datamodellen omfatter enheter som gassdetektorer, plattformer, anlegg, værfaktorer, objekttyper, katalogprofiler, funksjonsblokker og notifikasjoner, med tilknyttede attributter. Kildesystemene som brukes i oppgaven inkluderer Aveva Net og SAP for lagring og administrasjon av utstyrsinformasjon og vedlikeholdsdata, samt sikkerhets- og automatiseringssystem (SAS) for hendelser og alarmer knyttet til gassdetektorer. CDF muliggjør integrering og sammenkobling av data fra ulike kilder, og data fra alle nevnte kilder er allerede tilgjengelige i CDF-datasett.

Datamodellen er implementert i CDF, men det oppstod utfordringer med å knytte data til datamodellen. Videre arbeid blir foreslått, inkludert integrering av gassdetektorenes diagnostiske alarmer og hendelser, notifikasjoner og værdata i datamodellen, samt bruk av den for prediktivt vedlikehold og analyse av forholdet mellom gassdetektorer og værforhold.

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Code Listings

Abbreviations and Symbols

λ	probability of failure
μm	micrometre
τ	interval of function test
A2	fire detection area on ULP
API	application programming interface
APIM	Azure API management
APOS	Automated process for follow-up of safety instrumented systems (Norwegian: Automatisert prosess for oppfølging av instrumenterte sikkerhetssystemer)
CCR	central control room
CDF	Cognite Data Fusion
CEN	European Committee for Standardization
CMB	condition-based maintenance
CMMS	computerised maintenance management system
DD	dangerous detected
DU	dangerous undetected
E2E	end to end
EN	European Standard
ESD	emergency shutdown
F&G	fire and gas
FDM	Flexible Data Modeling
FLOC	Functional Location
FPSO	floating production storage and offloading
GDL	gas detector line
GL	guideline
HSI	human system interface
HVAC	heating, ventilation, and air conditioning
IEC	International Electrotechnical Commission

IEEE Institute of Electrical and Electronics Engineers
IR infrared radiation
ISO International Organization for Standardization
IT information technology

LCI life cycle information
LEL lower explosion limit
LELm lower explosive limit meter
LOO low output

M2 Malfunction report
mA milliampere
MA_FG Monitoring of analogue process variables - fire and gas
MET Norwegian Meteorological Institute

NORSOK the Norwegian shelf's competitive position (Norwegian: Norsk Sokkels Konkurranseposisjon)
not notification
NTNU Norwegian University of Science and Technology

OPC UA Open Platform Communications Unified Architecture
OT operational technology

PAS publicly available specification
PDS reliability of SIS (Norwegian: pålitelighet i datamaskinbaserte sikkerhetssytsemer)
PFD probability of failure on demand
PM plant maintenance
PP PostProcessor
PSA Petroleum Safety Authority

R receiver
RAMI 4.0 Reference Architectural Model Industry 4.0
RBD reliability block diagram
RNNP trends in risk level in the petroleum activity (Norwegian: risikonivå i norsk petroleumsvirksomhet)

S safety
SAP Systems, Applications, and Products in Data Processing
SAS safety and automation system
SD safe detected
SIF safety instrumented function
SIL safety integrity level
SIS safety instrumented system
SN Standards Norway
SQL structured query language

SRS safety requirement specification
SU safe undetected

UEL upper explosion limit
ULD Ula drilling platform
ULP Ula production platform
ULQ Ula living quarters platform

ZVEI German Electrical and Electronic Manufacturers' Association (German: Zentralverband Elektrotechnik- und Elektronikindustrie e.V.)

Preface

This master thesis was written as a part of the study program Cybernetics and Robotics during the spring semester of 2023. The study program is based in the Department of Engineering Cybernetics at the Norwegian University of Science and Technology (NTNU). The thesis was carried out in collaboration with Aker BP.

The primary focus of the thesis is to investigate the feasibility of implementing predictive maintenance for optical gas detectors. This is achieved through the development of a data model that analyses detector faults and weather conditions. Historical data from various Aker BP systems are utilised to implement the data model in Cognite Data Fusion (CDF). The initial objective of the thesis was proposed by Aker BP and further refined through discussions with supervisors from Aker BP and NTNU. It is assumed that the reader possesses some knowledge about safety instrumented system (SIS).

Trondheim, 5th June 2023

Birgit Salomonsen Øygard

Chapter 1

Introduction

1.1 Background

Offshore facilities rely on fast and reliable notifications and alarms from gas detectors in case of gas leakages. Unfortunately, gas detectors are susceptible to report errors and false alarms due to for example certain weather conditions that cause dirty optics. According to Håbrekke and Onshus, 2017, the Petroleum Safety Authority (PSA) has expressed doubts regarding the effectiveness of optical gas detectors in the presence of moisture, water, snow and similar elements based on several incidents. As a part of a safety instrumented system (SIS), gas detection constitutes an important safety barrier on offshore facilities and is therefore of high priority. Gas detector maintenance is mostly reactive, resulting in instrument technicians being obstructed from their intended work when gas detectors unexpectedly malfunction. The work of cleaning detector lenses takes a lot of time that may be saved if one could predict or understand when detector fault behaviour can be expected.

One of the incidents mentioned in Håbrekke and Onshus, 2017 involved a hydrocarbon leakage combined with the release of hot water due to a break in the water outlet on a separator. The leak resulted in generation of hot steam and gas on the production platform. As described by Nilsen, 2018 and Håbrekke and Onshus, 2017, two types of gas detectors were installed at the facility. The transition was made from catalytic bead gas detectors to modern infrared radiation (IR) gas detectors. During this particular event, it was observed that the IR gas detectors reported faults, which caused a delay in detecting the gas concentration compared to the catalytic detectors. Despite the delay, the IR gas detectors would have provided faster alarms than the catalytic detectors if certain logic had been implemented. This logic could for example have ensured the initiation of a shutdown in the event of a failure of five detectors. The release of hot water is not a weather condition but the situation demonstrates that optical gas detectors are significantly affected negatively by external effects. This has to be dealt with in the design phase.

Data related to gas detector measurements are collected from the safety and automation system (SAS). If such data could be combined with data about events and activities leading to dirty optics, like weather data, it could provide more efficient scheduling and selection of gas detectors for the next maintenance through the work order system in Systems, Applications, and Products in Data Processing (SAP), which is Aker BP's computerised maintenance management system (CMMS). Data about previous maintenance of the gas detectors could also shed more light on the relation between environmental conditions and diagnostic alarms. Today, the SAS, SAP and weather systems are among data sources feeding data to the Cognite Data Fusion (CDF) cloud platform used by Aker BP. Unfortunately, there is currently no available specification or realisation of a data model that exploits the mentioned data sources in CDF.

A data model that utilises historic diagnostic alarms, events, notifications, and weather data for gas detectors can predict the impact of weather conditions on their performance ensuring proper and possibly improved barrier management for this important safety barrier. Using this tool to plan lens washing tasks can help reduce gas detector downtime. Furthermore, planning detector maintenance can ensure that the necessary workers are available and prevent disruptions to other maintenance activities. The data model can also provide a better understanding of problematic areas and identify bad actor where redesign or replacement of detection principles can be considered. With advance information about activities and conditions that are likely to cause gas detector failure, preventive maintenance can be planned and executed more cost-effectively during periods where dirty optics are expected. As this possibility has not been fully explored, creating such a data model would be beneficial.

Reference Architectural Model Industry 4.0 (RAMI 4.0) provides a standardised approach for the design and implementation of cyber-physical systems in industrial settings. As part of this framework, data models can be used to define the structure, format, and semantics of the data that is exchanged and shared between different entities within the system. Analysing the data model within the RAMI 4.0 framework can help aligning the data model with the overall goals and requirements of the industrial application. Therefore, RAMI 4.0 can be used as a guiding framework for designing and analysing the data model.

1.2 Objective

The objective of this master thesis is to create a data model for monitoring of optical gas detectors and pilot its implementation in CDF using historical data from Aker BP systems. The data model will exploit various data sources for diagnostic alarms and events, notifications, and weather data, with the purpose of improved maintenance planning. Five research activities will be performed to ensure the thesis objective:

1. Familiarise with and present the use case associated with SIS follow-up of optical gas detectors, including data collection and analysis for condition-

monitoring and failure predictions, and prepare a use case specification detailing the problems to be solved and decision-making.
2. Identify data and information that are needed to construct a data model considering the use case. Prepare a requirement specification that an implementation of the data model must satisfy following steps from RAMI 4.0 and relevant standards within software development.
3. Implement the data model using Flexible Data Modeling (FDM) in CDF, involving the generation of suitable information models, connection to underlying source systems, and illustrate the information that can be extracted when data are combined.
4. Discuss the results including to what extent it is able to meet the use case specification.
5. Identify areas and topics of further research and investigation.

1.3 Approach

The theory on SIS is built on the literature study conducted in the specialisation thesis during the autumn semester of 2022. Apart from that this master thesis is an independent project.

The specialisation thesis was a part of the Automated process for follow-up of safety instrumented systems (Norwegian: Automatisert prosess for oppfølging av instrumenterte sikkerhetssystemer) (APOS) project. This has involved meetings with researchers from SINTEF, as well as the opportunity to attend reliability of SIS (Norwegian: pålitelighet i datamaskinbaserte sikkerhetssytsemer) (PDS)-forum meetings. PDS-forum serves as a venue where control and safety system vendors and users come together to share their experiences. The main emphasis is placed on discussing the safety and reliability elements associated with these systems (SINTEF, 2023). The author has actively taken part in PDS-forum meetings throughout the writing period for both the specialisation project and the master thesis. This has been helpful for acquiring a better understanding of SIS and RAMI 4.0.

The collaborative aspect of the master thesis involves Aker BP, including regular meetings with supervisors. Aker BP granted access to their systems and historical data, as well as offering a network of specialists who were available to provide assistance and answer inquiries.

Figure 1.1 presents a method to establish a data model, comprising several sequential steps. The initial stage involves specifying the use case. Identifying the questions necessary for achieving the use case goals follows as the subsequent step. This involves determining the specific knowledge requirements. Moving forward, the third stage involves describing the information that addresses these questions. Once this characterisation is complete, the final step entails locating the relevant data sources that contain the required information.

The data model is to follow a three-stage process in line with the architecture layers dimension of the RAMI 4.0; the layers are shown in Figure 1.2 and

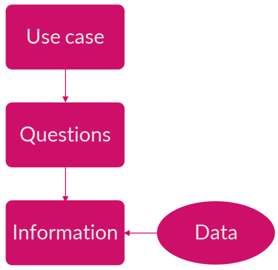

Figure 1.1: Steps for developing a data model.

explained in Section 3.1.2. This will be done by following the stages specified in Table 1.1. The stages harmonise with the steps specified in Figure 1.1 and connect the research activities from the objective to the RAMI 4.0 layers.

Figure 1.2: The architecture layers of the RAMI 4.0.

In order to create the data model specifications, the standards IEC 12207, 2017 and IEC 15288, 2015 were considered together with the guidelines for the application of these standards, found in IEC 24748, 2018 and IEC 29148, 2018. IEC 15288, 2015 *Systems and software engineering – System life cycle processes* was chosen over IEC 12207, 2017 because it considers system life cycle processes. This is more applicable than software life cycle processes which is covered in IEC 12207, 2017, since the data model must also consider physical systems. The two International Electrotechnical Commission (IEC) standards are harmonised.

IEC 15288, 2015 contains four main system life cycle processes. This master thesis only considers the last of these processes, the technical process. The excluded processes regard agreement, organisational and management processes that are to a great extent fulfilled by the master thesis format. The technical process consists of many processes concerning the whole life cycle of a system, from conception to disposal. Four of these processes are used together with the RAMI 4.0 for developing the specifications in this master thesis. An additional three technical processes are used for further development of the data model. The following list contains the IEC 15288, 2015 processes used in this master thesis.

Table 1.1: Three-stage process

Level	Research activities and questions
Business and functional	Define the use case, with focus on what problems are to be solved and what decisions are to be made.
Information and communication	Find which information that is needed and in which systems it can be accessed.
Integration and asset	Specify the data model, including information models organising and combining data, connecting data to source systems (assets).

- Business or mission analysis process
- System requirements definition process
- Architecture definition process
- Design definition process
- System analysis process
- Implementation process
- Integration process

1.4 Limitations

When engaging with real systems, it is common to encounter practical challenges. In this case, a specific challenge was that the integration of Aker BP data into CDF occurred simultaneously. As a result, the required data was not initially accessible but gradually became available during the writing period. Furthermore, it is important to note that CDF is an evolving product. The introduction of FDM started with a public beta-tool in November 2022 and was subsequently made widely accessible in April 2023. Working on this thesis involved encountering numerous updates, which presented a challenge in dealing with Cognite Data Fusion (CDF). However, these updates also enhanced the functionality of CDF and facilitated progress.

Cyber security is not addressed in this thesis. However, it is important to acknowledge that data security and privacy are crucial considerations when working with operational data. In this case, it is assumed that Aker BP and Cognite have implemented appropriate measures to handle these aspects effectively.

1.5 Structure of the Thesis

The second chapter of this master thesis establishes the foundation for the use case by examining functional safety. Furthermore, it explores gas detectors and their different detection principles. In the third chapter, the focus shifts towards smart systems and maintenance, explaining RAMI 4.0 and maintenance theories such as predictive maintenance. The fourth chapter introduces Aker BP, providing essential details about their assets, systems, tag structure, and relevant projects. Moving on to the fifth chapter, it concentrates on the data and data tools employed in this thesis, including the data source systems. This chapter emphasises the functionality of CDF. Chapter six presents the use case and outlines the requirement specifications. The seventh chapter delves into the CDF data sets and the implemented data model in CDF, while the eighth chapter discusses the implications of the model. Finally, chapter nine concludes the thesis and proposes future research.

Chapter 2

Gas Detection and Safety

2.1 Functional Safety

2.1.1 SIS

As an important part of the safety barriers on a facility, a SIS carries out designated safety functions through various safety instrumented function (SIF)s. For example, one SIF could be the detection of gas, as depicted in Figure 2.2 and a SIS could be made up of a number of gas detection SIFs. The primary purpose of these safety functions is to prevent hazardous situations by promptly responding to abnormal conditions (PSA, 2021). In the event of an accident, SIFs are designed to mitigate any potential damage. Their operation involves early detection and response to abnormal conditions before they escalate into hazardous situations.

SIFs typically consist of three essential components: an input component, a logic solver, and an output component. The input component is responsible for detecting and sensing abnormal conditions, while the output component generates the final response. The logic solver contains the activation rules for the function. By examining the signals from the input component, it triggers the output component when the input meets the criteria for abnormal conditions. SIFs can incorporate multiple input and output elements as well.

2.1.2 Standards and Regulations

Functional safety aims to reduce inherent risks to an acceptable level, particularly in hazardous industrial processes, through the use of automated safety functions. The systems responsible for implementing these functions are covered in the horizontal standard series, IEC 61508, 2010 *Functional safety of electrical/electronic/-programmable electronic safety-related systems - Part 1: General requirements*. This standard provides a risk-based approach to determine safety system performance requirements throughout their life cycle, including their components and related software.

To determine requirements for risk reduction, potential hazards must be ana-

Table 2.1: Failure classes

Failure class	Description
Safe detected (SD)	A failure that is revealed by diagnostics; the system will remain in a safe state.
Safe undetected (SU)	A failure that is not revealed by diagnostics; the system will remain in a safe state.
Dangerous detected (DD)	A failure that is revealed by diagnostics; the system will enter an unsafe state.
Dangerous undetected (DU)	A failure that is not revealed by diagnostics; the system will enter an unsafe state.

lysed for a given system. The IEC 61508, 2010 standard defines safety integrity level (SIL) as a measure of function reliability, which can be set based on the likelihood and severity of potential consequences. There are four SIL levels, and the average probability of failure on demand (PFD) for a SIF is used to measure its achieved SIL. The PFD encompasses dangerous undetected (DU) failures. This is one of four failure classes, shown in Table 2.1. Only the dangerous failures will impact the risk since SD and safe undetected (SU) failures do not lead to hazardous situations. Dangerous detected (DD) failures are detected and will therefore be corrected before the SIF is activated. A detector with dirty optics is still operational, an dirty optics is therefore a SD failure. When a detector becomes beam blocked, it is no longer functional and beam block can be considered a DD failure.

The industry standard for the process industry sector, IEC 61511, 2017 *Functional safety - Safety instrumented systems for the process industry sector - Part 1: Framework, definitions, system, hardware and application programming requirements,* is based on IEC 61508, 2010 and covers SIFs, which represent the automated safety functions from IEC 61508, 2010. IEC 61511, 2017 builds on the risk-based approach for determining SIL requirements. The standard also defines a SIS safety life cycle model. Figure 2.1 shows the model, with three phases omitted. The omitted phases are functional safety assessment, safety life cycle structure and planning, and verification phases. These phases affect all of the other phases in the life cycle and are essential parts of the SIS safety life cycle.

The SIS safety life cycle is a framework that defines the necessary activities for implementing SIFs during the SIS lifetime (IEC 61511, 2017). Each phase of the safety life cycle has a defined set of inputs and outputs, and verification should be performed at the end of each phase to ensure that the required outputs meet the specifications. This helps to ensure that the SIS is implemented as intended and that the required SIL is achieved. The safety life cycle also provides a structured approach to manage the safety aspects of a SIS, from concept to decommissioning, and ensures that the SIS remains safe and reliable throughout its operational lifetime.

Several factors must be considered when designing, installing, and commissioning a gas detection SIF. The hazard and risk assessment in the initial phase

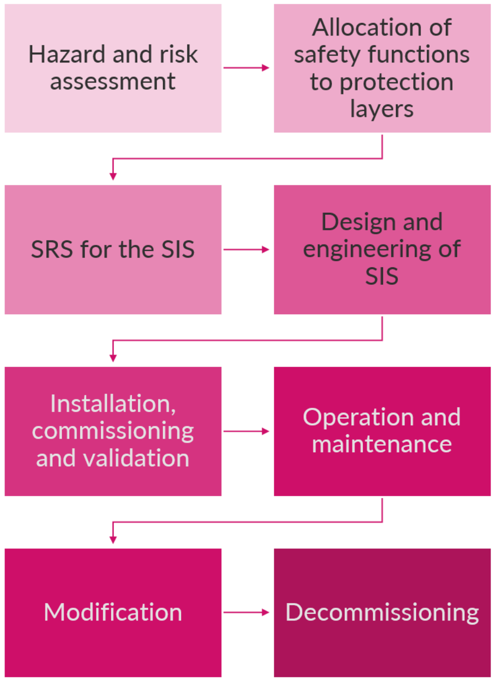

Figure 2.1: SIS safety life cycle, adapted from IEC 61511, 2017.

is a critical step in identifying the required safety functions and associated risks. The allocation of safety functions to protection layers, SIFs, is then decided and assigned their associated SIL. The safety requirement specification (SRS) is a document that outlines the safety requirements for the SIS, including the SIFs and their safety integrity to ensure that the required functional safety is achieved.

In the design and engineering phase, the SIS is designed so that the SIL requirements for the SIFs are met. This is a crucial step in ensuring that the SIS can function safely and effectively. The installation, commissioning, and validation phase then follows, which encompasses integration, testing, and validation of the SIS. This is done to ensure that the SIS functions as intended and meets the specified safety requirements.

During the operation and maintenance phase, it is essential to maintain the functional safety of the SIS. This involves regularly checking and maintaining the SIFs and ensuring that they meet their associated SIL. This requires monitoring of failure rates and PFD verification. The modification phase is also important as it ensures that the SIS safety requirements are still met in the event of a change to the SIS. Finally, the decommissioning phase involves reviewing the SIS to ensure that it is safe to decommission and that all necessary measures have been taken to ensure safety during the decommissioning process.

In Norway, safety functions are regulated by the PSA regulations, which require facilities to be equipped with necessary safety functions and for safety function performance requirements to be in place PSA, 2021. The PSA recommends using the IEC standards, the standard NORSOK S-001, 2021, and also the guideline (GL) document Offshore Norway, 2022 'Application of IEC 61508 and IEC 61511 in the petroleum activities on the continental shelf (Recommended SIL requirements)' for determining safety function requirements. Offshore Norway, an industry association, has standardised SIFs for the Norwegian petroleum industry, which can be used in place of the risk-based approach for determining requirements. The Norwegian standard NORSOK S-001, 2021 outlines the principles and requirements for the technical safety design of offshore installations used in the production of oil and gas. It covers the development of physical safety measures for such installations, including gas detection recommended practices for different installation areas.

The trends in risk level in the petroleum activity (Norwegian: risikonivå i norsk petroleumsvirksomhet) (RNNP) refers to the assessment and evaluation of the potential risks associated with oil and gas exploration, production, and related operations in the petroleum industry in Norway. The risk level in Norwegian petroleum activity is regularly monitored and analysed to identify potential hazards and vulnerabilities. The aim is to prevent accidents, incidents, and major environmental impacts. The risk level is influenced by factors such as the complexity of operations, the integrity of equipment and infrastructure, human factors, and external threats such as extreme weather conditions. As stated in PSA, 2023, PSA evaluates the risk level development by employing two methods: a quantitative measurement tool and sociological analyses. The operating companies are required to actively contribute data regarding activities at the facilities (PSA, 2023). The companies must therefore manage equipment failures during the SIS operation and maintenance phase for reporting to RNNP. The result of the RNNP process is yearly published as a two-part report.

2.1.3 Gas Detection SIF

The primary function of the gas detection system is to provide continuous monitoring for the existence of flammable or toxic gases (NORSOK S-001, 2021). Its purpose is to promptly notify personnel and enable the initiation of control measures, either manually or automatically. This is done to minimise the likelihood of personnel being exposed to harmful gases, as well as to mitigate the risks of explosions and fires.

A gas detection SIF is a part of the gas detection system designed to detect the presence of hazardous gases in an industrial facility or process. The SIF activates an alarm or initiates an automated response to protect personnel, equipment, and the environment from harm. According to PSA, 2021, all facilities must be equipped with a fire and gas detection system that ensures reliable and fast detection of fires, fire outbreaks and gas leaks. NORSOK S-001, 2021 also stipulates that gas detectors must be installed in all areas where hazardous gas concentrations may be present. When designing a detection system for an area, several factors must be taken into consideration, including detector coverage, detector charac-

Table 2.2: Potential alarm limits for the analogue output of a line gas detector, from Håbrekke and Onshus, 2017.

mA	Alarm
0	No signal
0-1.5	Fault
1.6-3.0	Beam block
3.1-3.9	Dirty optics
4.0	Zero gas
4.0-20	Gas [LELm]
>20	Fault

teristics, number and location of detectors, and external effects such as weather, wind, and radiation.

Figure 2.2 shows the reliability block diagram (RBD) for a gas detection SIF with one detector. The SIF is defined in Offshore Norway, 2022. It consists of a gas detector as the input and a fire and gas (F&G) node. When the detector or detector beam is exposed to gas, the function starts. The gas detector generates an analogue 4-20 mA signal representing the amount of gas detected in the air concentration. Analogue signals below and above 4-20 mA are used for diagnostic alarms and could for example be configured like in Table 2.2. The logic solver processes the signal, generates an action signal and the action signal transmitted from the F&G system ends the function. The logic of the F&G detection system can be configured in different ways depending on for example the implemented voting and the location of the detectors that detect gas (Offshore Norway, 2022). Detector layout and the number of detectors must also be considered. The reason for detected gas could for example be gas leakage from a pipeline or a fire. This SIF does not have a final element, but there exists other SIFs that include fire extinguishing systems and valves for closing gas-leading pipelines. The F&G logic could be configured to send action signals that initiate other SIFs, like emergency shutdown (ESD).

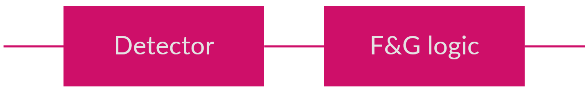

Figure 2.2: RBD for gas detection with one detector SIF, adapted from Offshore Norway, 2022.

The gas detection SIF not only handles action signals but can also perform diagnostics, generating alarm signals as part of its functionality. These diagnostics involve continuous monitoring of the gas detectors' performance and providing real-time feedback on their status. Through this process, failures such as SD and DD are detected. The diagnostic capability of the system is crucial in ensuring that gas detectors operate correctly and reliably detect the presence of hazardous gases. It enables the detection of potential issues and malfunctions, allowing for timely maintenance and intervention.

To ensure operator awareness and facilitate appropriate action, the gas detection alarms and the overall status of the F&G system should be continuously available in the central control room (CCR) (NORSOK S-001, 2021). The system should raise alarms in the CCR, notifying operators of any gas detection events, failures to execute required actions, or defects or failures within the system's components. Moreover, it is essential that the status and alarm parameters for each individual gas detector are identifiable and displayed in the CCR. This information allows operators to monitor the status of each detector and take appropriate actions based on the presented data.

The gas detection SIF depicted in Figure 2.2 is required to have a minimum SIL of 2, as specified by Offshore Norway, 2022. SIL 2 is the second lowest SIL among the four levels defined in the standard. The likelihood of the SIF failing to execute its safety function due to a DU fault depends on the system's probability of DU failure (λ_{DU}) and the frequency of function testing (τ). Offshore Norway, 2022 provides a simplified formula:

$$PFD \approx \frac{\lambda_{DU} * \tau^2}{2} \tag{2.1}$$

To reduce the risk and meet the SIL requirement, λ_{DU} or τ must be decreased. SIFs should be regularly tested to confirm their ability to perform their intended safety function. Reducing the time between these function tests will decrease the PFD. The probability of a system DU failure can be lowered by reconfiguring the system, such as by implementing component redundancy or using components that are more dependable.

According to (Offshore Norway, 2022), the SIF safe state is a signal generated by the F&G logic. It represents a state that ensures inherent safety within a system, which can include actions like initiating the ESD. In the event of a power or signal loss from the detector or the F&G system, the gas detection SIF is designed to enter a safe state. This activation of the safe state actions occurs when there is a loss of power or signal; the function is de-energised to safe state (Offshore Norway, 2022).

There are specific requirements for the response time of the SIF. The response time of the F&G system must be fast enough to avoid dangerous situations, which depends on factors like the type of area and distance to ignition sources. The term T90, as described by Håbrekke and Onshus, 2017, refers to the response time of a detector. Specifically, it represents the time taken by the detector to measure 90% of the actual gas concentration in the air. NORSOK S-001, 2021 provides typical response time requirements for IR detectors and alarm presentation that should be followed unless faster responses are specified.

For general area applications, the recommended T90 response time for an IR detector is less than 5 seconds. If the IR detector is utilised in heating, ventilation, and air conditioning (HVAC) ducting, the T90 response time should be less than 2 seconds. This means that the detector should be able to achieve a 90% measurement of the actual gas concentration within the specified time frames.

Additionally, the duration between the detector reaching the alarm limit and the presentation of the alarm on the operator station, along with the initiation of subsequent actions, should be less than 2 seconds (NORSOK S-001, 2021). These guidelines and requirements aim to ensure the system's ability to detect, respond, and initiate appropriate actions promptly during hazardous situations, promoting safety and efficient operations.

2.1.4 SIS Follow-Up of Gas Detection SIF

During the operational phase of a SIS, ensuring adequate SIS performance is a key aspect that requires continuous monitoring and maintenance throughout its operational lifetime (Håbrekke, Hauge et al., 2023). The preparation phase starts during the design, installation, and commissioning of the SIS, while the execution phase covers the operation, maintenance, and modification phases of the SIS safety life cycle from IEC 61511, 2017. The main functional safety activities related to SIS during its operational phase, as identified by Håbrekke, Hauge et al., 2023, can be divided into the following activities:

- Management of functional safety
- SIS operation
- SIS maintenance
- SIS performance monitoring, verification, and analysis
- SIS management of change

Figure 2.3 depicts the connections between the activities.

Functional safety management is a crucial element in the SIS follow-up and is necessary across all stages of the safety life cycle. It encompasses the establishment and maintenance of policies, procedures, and processes aimed at effectively managing risks associated with functional safety (Håbrekke, Hauge et al., 2023). This encompasses planning and monitoring various activities to guarantee the sustained reliability and safety of gas detectors.

During the operational phase, normal interaction with the SIS involves monitoring its real-time status, conducting start-up and shutdown procedures, casually observing the SIS equipment, reporting identified failures, degraded states, and non-conformities, initiating maintenance requests or SIS modifications, implementing mitigating measures when the SIS is degraded or unavailable, and managing bypass settings, resets, and status tracking (Håbrekke, Hauge et al., 2023). Operators and personnel continuously monitor the SIS's real-time status, through diagnostics and alarms in the CCR, ensuring it operates properly. They follow specific procedures during start-up and shutdown to ensure controlled activation or deactivation. Regular visual checks are conducted to identify any physical damage or degradation. Any failures or non-conformities are promptly reported for appropriate action, including maintenance requests or modifications. Bypassing a SIF may be required to override, disable, or inhibit its operation tem-

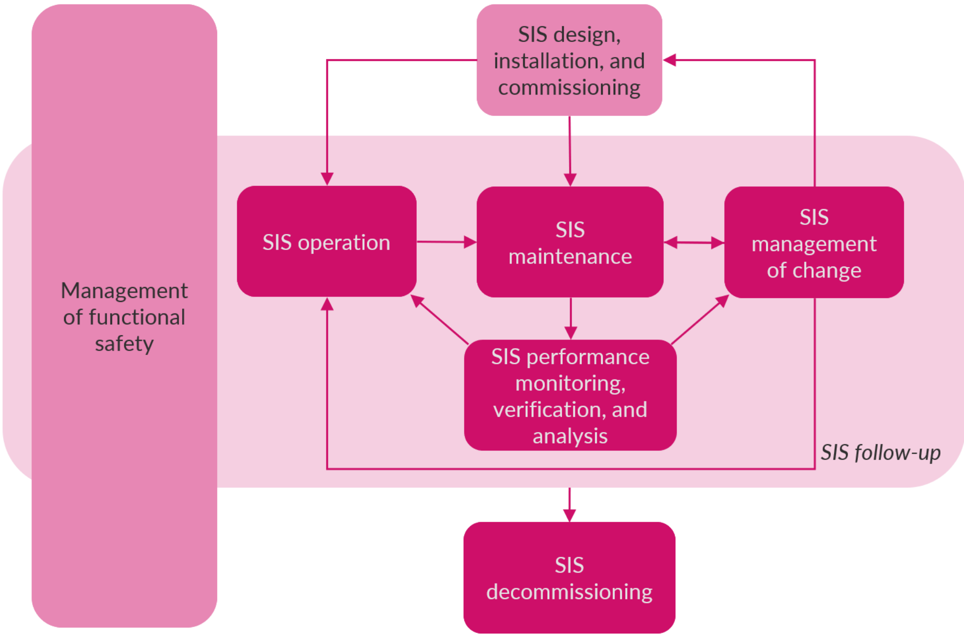

Figure 2.3: Main activities of SIS follow-up, adapted from Håbrekke, Hauge et al., 2023.

porarily, often to prevent process disturbances, such as during testing (Håbrekke, Hauge et al., 2023). Mitigating measures are implemented if the SIS is degraded or unavailable, and bypasses are managed, tracked, and reviewed to maintain safety. These interactions ensure the SIS's effectiveness and contribute to a safe operational environment.

The maintenance activities for SIS in the operational phase include scheduled function testing, inspections, failure recording, repair, overhaul, and replacements (Håbrekke, Hauge et al., 2023). Additionally, simple consequence analysis and failure cause analysis, such as root cause analysis or 5-why analysis, are conducted to identify mitigating measures. Regular function testing and maintenance of the SIS are essential and should be performed in accordance with the SRS and as specified in the CMMS (Håbrekke, Hauge et al., 2023). Function testing helps detect SD and DD failures. Furthermore, function testing is necessary after the replacement or installation of new components and after a firmware upgrade of logic solvers. These maintenance activities help maintain the system's integrity and compliance with safety standards.

SIS monitoring, verification, and analysis encompass the examination and validation of various performance requirements of the SIS. This includes evaluating parameters such as PFD, SIL requirements, failure rates, demand rates, and spurious trip rates (Håbrekke, Hauge et al., 2023). The DU failures discovered during function testing in the maintenance phase can be used to reevaluate the equipment PFD. This is necessary for SIL verification. It is important that the SIF remains within the SIL requirement. If the equipment reliability changes, it might require a change in the function test intervals in the SIS operation or a change in the SIS. The SIS management of change process focuses on planning, reviewing, approving, and documenting modifications to the SIS to maintain safety integrity (Håbrekke, Hauge et al., 2023). The verification process extends to verifying the output requirements of all activities throughout the facility's life cycle. Through continuous monitoring and verification, any potential issues or failures within the SIS can be promptly identified and addressed, ensuring its ongoing reliability and effectiveness in mitigating safety risks.

2.2 Gas Detectors

2.2.1 Gas Detection Principles

Design Principles

Gas detectors are commonly categorised into point detectors and line detectors based on the employed design principle (Håbrekke and Onshus, 2017). The gas detector SIF depicted in Figure 2.2 can be classified as either of these types. According to NORSOK S-001, 2021, a combination of point detectors and line detectors shall be utilised to ensure effective coverage and enhance the probability of detection. Gas detectors can also be classified according to the measuring principle they utilise (EN ISO 14224, 2016). Additionally, they can be distinguished as either traditional wired detectors or wireless gas detectors (Håbrekke and Onshus, 2017). Different measuring principles are compared in Table 2.3.

Point gas detectors, also known as single-point or spot gas detectors, are designed to monitor gas concentrations at a specific location (Håbrekke and Onshus, 2017). They are typically installed in areas where a potential gas leak or hazardous gas release is likely to occur. These detectors continuously monitor the air or the gas sample at the specific point of installation and provide real-time measurements of gas concentrations.

Line gas detectors, also referred to as open path gas detectors, line-of-sight gas detectors and beam detectors, are designed to monitor gas concentrations over a defined path or distance (Håbrekke and Onshus, 2017). They are used to detect gases across larger areas or in outdoor environments where the dispersion of gas may be more extensive.

IR line gas detectors consist of two main components: a transmitter and a receiver. IR point gas detectors encompass the transmitter and receiver in the same detector. The transmitter emits a beam of light, usually IR, ultraviolet, or laser, across the desired detection path. The receiver, located opposite the transmitter, receives the beam and measures the amount of light that reaches it. If there is a gas present along the detection path, it can absorb or scatter the emitted light, causing a reduction in the amount of light reaching the receiver. The receiver continuously monitors the received light intensity and analyses any changes.

Meauring Unit

Hydrocarbon/air mixtures have specific mixing ratios in which they can ignite. The lower explosion limit (LEL) represents the minimum concentration of the mixture that can ignite, while the upper explosion limit (UEL) represents the maximum concentration that can ignite (Håbrekke and Onshus, 2017). Any concentration within this range has the potential to ignite, making it crucial to measure and assess the risk of ignition. Gas detectors are designed to measure the concentration of gases in relation to the LEL value (Håbrekke and Onshus, 2017). The gas concentration is expressed as a percentage relative to the LEL. By monitoring the gas concentration and comparing it to the LEL, the detector can determine the potential risk of an explosive atmosphere. The unit of measurement for the gas concentration in the beam of a line gas detector is the product of the length of the gas cloud (measured in meters) that covers the beam and the average gas concentration expressed as a percentage of the LEL within that cloud: lower explosive limit meter (LELm) (Håbrekke and Onshus, 2017).

Catalytic Detection

A catalytic gas detector is a type of point gas detector designed to detect flammable gases by measuring the heat generated through catalytic oxidation (Håbrekke and Onshus, 2017). In this type of detector, a catalyst facilitates the reaction between the combustible gas and oxygen. This reaction generates heat, which in turn increases the temperature of a platinum resistor within the detector. By monitoring the temperature change, the detector can determine the presence and concentration of the flammable gas.

Catalytic gas detectors have certain drawbacks, which has led to their gradual phase-out on the Norwegian continental shelf. However, it is worth noting that many catalytic gas detectors are still in operation. These detectors require regular calibration, usually every four months or even more frequently. Additionally, catalytic gas detectors have a longer T90 response time, typically less than 25 seconds, compared to other types of detectors such as optical detectors, which typically have a response time of less than 5 seconds (Håbrekke and Onshus, 2017).

One of the significant safety disadvantages of catalytic detectors is their tendency to fail without warning (Håbrekke and Onshus, 2017). They lack self-diagnostic capabilities beyond basic loop monitoring, which means they are unable to provide feedback on their own operational condition. This poses a challenge as they cannot indicate whether they are malfunctioning, degraded, or completely non-functional.

Due to these limitations, there has been a shift towards alternative gas detection technologies, including optical detectors, which offer faster response times and improved self-diagnostic capabilities. As per NORSOK S-001, 2021, it is stated that hydrocarbon detectors, particularly IR detectors, equipped with self-diagnostics and suitable for the specific gas to be detected, should be employed. The standard further states that catalytic detectors should only be considered if other types of detectors fail to meet the required detection performance.

Table 2.3: Advantages and disadvantages of different gas detector types, based on Håbrekke and Onshus, 2017 and Nilsen, 2018.

Gas detector type	Advantages	Disadvantages
Catalytic detector	Simple and cheap Responds to gas even under "extreme conditions" such as hot water vapour (steam)	Lack of self-diagnosis High DU error rate Frequent need of test Must be calibrated often Long response time
IR detector	Good self-diagnosis Fast response Reacts to hydrocarbon gases in general Heated optics	Fails due to moisture/ condensation on lens High spurious trip rate: Often fails due to snow, fog, etc.
Laser detector	Good self-diagnostics Fast response High sensitivity (detection of low gas concentrations) Low spurious trip rate (even in rain, snow, fog, etc.) Gas-specific: Calibrated for predefined gas(es) Long test interval	Gas-specific Expensive
Acoustic detector	Good self-diagnosis High sensitivity (detection of small leaks) Not dependent on temperature, weather and wind conditions Covers a large area	Does not detect moist gas, gas with water (best suited for dry gas) Sensitive to background noise Difficult to locate the leak point

Optical Detection

An optical gas detector, specifically an IR detector, is a type of gas detector that can function as a point gas detector or a line gas detector (Håbrekke and Onshus, 2017). It detects hydrocarbon gases by emitting IR rays, at two different wavelengths, from a transmitter to a receiver.

The two wavelengths used in the detector are the measurement wavelength and the reference wavelength (Håbrekke and Onshus, 2017). The measurement wavelength is chosen to coincide with the specific vibrations in the molecules of the hydrocarbon gas being targeted. As a result, the gas absorbs light at this particular wavelength.

The IR source in the detector can be either a lamp or a laser (Håbrekke and Onshus, 2017). It emits the IR rays at the designated wavelengths, and these rays are directed towards the receiver. The receiver then measures the intensity of the received IR light at the measurement wavelength and compares it to the reference wavelength.

By analysing the difference in intensity between the two wavelengths, the optical gas detector can determine the presence and concentration of the hydrocarbon gas (Håbrekke and Onshus, 2017). This detection principle is based on the specific light absorption characteristics of the targeted gas, allowing for accurate gas detection.

Typically, optical gas detectors undergo testing once a year, but they possess a relatively high level of self-diagnostic capabilities (Håbrekke and Onshus, 2017). In these detectors, the light intensity of the IR beam that reaches the receiver is converted into an electrical current, ranging from 0 to over 20 mA.

The measurement range of the gas concentration is usually set between 4 to 20 mA, while currents below or above this range are dedicated to fault alarming. The specific intervals and alarm limits at which the detector must respond can vary depending on the detector type and can be adjusted to some extent by the operator.

In general, a current signal within the range of 0-4 mA indicates a fault condition, beam blockage, or dirty optics, signalling a potential issue with the detector's functionality. On the other hand, a signal above 4 mA indicates the detection of gas, with the current level proportional to the gas concentration, typically measured in terms of the LELm, ranging from 0% to 100%, for line gas detectors.

Optical gas detectors using laser are highly resistant to various weather conditions such as snow and fog, as well as external influences like plastic, making them robust in challenging environments (Håbrekke and Onshus, 2017). They exhibit fewer false alarms, such as "beam block" or "dirty optics" alarms, compared to traditional IR line gas detectors.

Laser detectors are commonly utilised to measure specific gases or a limited range of gases. As a result, the detectors may not be suitable for detecting or measuring hydrocarbon gases outside their calibrated range (Håbrekke and Onshus, 2017). If there is a need to monitor additional or different hydrocarbon gases, alternative detection methods or detectors calibrated for those specific gases should be employed.

Gas-specific detection offers several advantages, including the ability to avoid false alarms and unexpected alarms from other gases (Håbrekke and Onshus, 2017). It allows for precise identification of the gas that has been detected, providing valuable information for response and mitigation efforts. However, this specificity can also pose a disadvantage in areas where multiple types of gases are present.

In environments with various gases, a laser gas detector calibrated for a specific gas might only trigger an alarm if that particular gas is detected. Other gases present in the environment will not result in a gas alarm or a fault alarm since the laser detector is not calibrated to recognise them. This limitation can potentially leave other gas hazards undetected, creating a safety risk.

Acoustic Detection

An acoustic or ultrasonic gas detector is a type of point gas detector that utilises ultrasonic technology to detect gas leaks. It operates by measuring the ultrasonic noise emitted by gas leaks from pressurised systems (Håbrekke and Onshus, 2017). This ultrasonic noise is generated at frequencies that are too high to be detected by the human ear.

One of the notable advantages of acoustic detectors is their ability to detect gas leaks regardless of wind direction and the dispersion of the gas (Håbrekke and Onshus, 2017). Unlike some other detection methods, the performance of acoustic detectors is not significantly affected by factors such as wind patterns. This allows for reliable detection even in outdoor environments or areas with airflow.

Another advantage is that acoustic detectors are capable of detecting small gas leaks (Håbrekke and Onshus, 2017). This high sensitivity enables the early detection of small leaks before they potentially escalate to higher rates or concentrations. By providing an "early warning," acoustic detectors help prevent the escalation of gas leaks and facilitate prompt mitigation measures.

Additionally, acoustic detectors are equipped with self-diagnostic capabilities (Håbrekke and Onshus, 2017). These self-diagnostics enable the detector to monitor its own condition, ensuring that it is functioning properly and providing reliable gas leak detection.

2.2.2 Functionality Under Extreme Conditions

Most IR point gas detectors operate based on a principle that uses a measurement wavelength of approximately 3.3 μm and a reference wavelength of around 3.0 μm. However, this specific wavelength range is susceptible to the effects of moisture and water. Håbrekke and Onshus, 2017 shows that water absorbs a significant portion of radiation within this wavelength spectrum.

In situations such as fog or snow, "dirty optics" alarms frequently occur in many detectors (Håbrekke and Onshus, 2017). This is due to the reduced light intensity of both the measurement signal and the reference signal when water absorbs the wavelengths used for measurement and reference.

Håbrekke and Onshus, 2017 specifies that "dirty optics" alarms are not treated as faults in the detectors themselves, as the detectors are still operational but require maintenance. Consequently, these alarms do not trigger automatic shutdown in the event of a detector fault or automatic changes in voting. Their purpose is to indicate the need for maintenance or cleaning rather than signalling a critical malfunction.

To mitigate the impact of moisture, IR detectors typically incorporate heated lenses (Håbrekke and Onshus, 2017). These lenses help compensate for the presence of moderate amounts of water, water film, fog, and similar factors. Additionally, many detectors are designed with weather housings around the measuring chamber. This arrangement serves to direct water outside of the IR beam, reducing the potential interference caused by water droplets.

Some IR detectors also come equipped with additional protective features such as "deluge protection" and "dust barriers" (Håbrekke and Onshus, 2017). These features help prevent water from entering the measuring chamber by deflecting droplets away from the detector. As a result, the detectors remain operational even in challenging weather conditions, including situations with high wind and rain.

The overall experience suggests that IR point gas detectors are more resilient to extreme weather conditions compared to line gas detectors (Håbrekke and Onshus, 2017). While the latter types may be more prone to failure in adverse weather, IR point gas detectors tend to maintain their functionality and reliability.

Chapter 3

Smart Systems and Maintenance

3.1 Reference Architectural Model Industry 4.0

3.1.1 Industry 4.0

Industry 4.0 refers to the fourth industrial revolution. In the third revolution, industries were revolutionised by the use of computers and automation. The ongoing, fourth revolution is based on network technology, where the internet of things enables machine-to-machine communication and digitalised production. Plattform Industrie 4.0, 2023b points out some of the advantages Industry 4.0 brings. One of these is the possibility of predictive maintenance by combining and analysing data from product and process monitoring.

RAMI 4.0 is a three-dimensional layer model describing the central features of Industry 4.0 (Hankel and Rexroth, 2015). The dimensions are shown with the three axes of Figure 3.1 and will be reviewed in the following subsection. Assets are central in industries, and also for Industry 4.0. Plattform Industrie 4.0, 2023a defines an asset as any resource that is owned or controlled by an organisation and is considered to have an actual or perceived value to the organisation. According to IEC PAS 63088, 2017, RAMI 4.0 gives a structured view of different aspects for assets and combinations of assets. It enables comprehensive descriptions of assets and breaking down complex processes or combinations of assets, into more manageable sections. The three-dimensional layer model provides a common foundation for structuring requirements and standards (Hankel and Rexroth, 2015). Establishing standards for communication and semantics that are universally accepted across companies and industries is important for development of Industry 4.0 (Plattform Industrie 4.0, 2018). A digitised industrial production requires common information models and secure communication protocols.

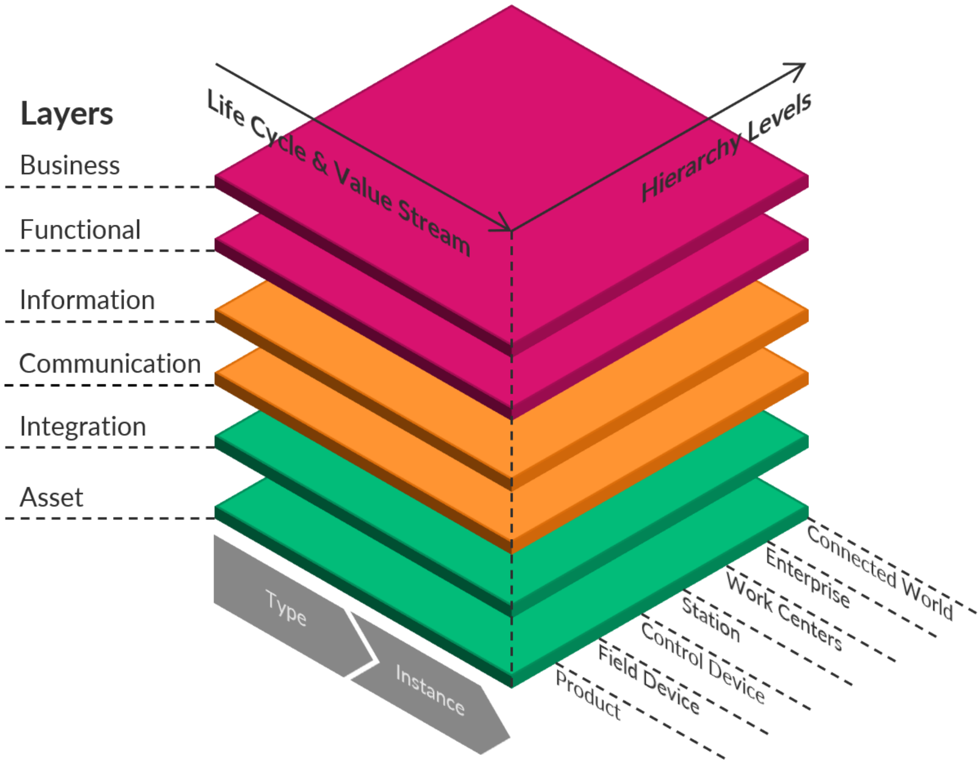

Figure 3.1: The three axes of RAMI 4.0, adapted from IEC PAS 63088, 2017.

3.1.2 RAMI 4.0 Structure

Architecture

The "Layers" axis describes the asset architecture by separating the structural properties in layers that describe different aspects of the asset (IEC PAS 63088, 2017). Table 3.1 lists the architecture layers, gives a definition from IEC PAS 63088, 2017 and includes an example of how the layers describe a gas detection SIF. The business, functional, information and communication layers are all represented in the digital world, while the asset layer is represented in the physical world. The integration level connect the asset layer with the digital layers through the integration layer.

At the top, the business layer focuses on strategic goals, requirements, and encompassing business models and processes (Sino-German Industrie 4.0, 2018). It provides a clear understanding of the organisation's objectives within the context of Industry 4.0. Next, the functional layer describes the asset functionality. It encompasses formal descriptions of functions, along with rules and decision-making logic (Sino-German Industrie 4.0, 2018). This layer defines how the assets operate and interact to fulfil the desired tasks and objectives. The Information Layer is responsible for managing the necessary data required for the asset functions (Plattform Industrie 4.0, 2018). It includes data models and structures that facilitate the exchange and processing of information within the system. The Communication Layer outlines how assets can access each other's functions and information (IEC PAS 63088, 2017). It defines the communication protocols, interfaces, and mechanisms necessary for seamless data exchange and coordination between assets. The integration layer focuses on digitalization and the integration of components (Plattform Industrie 4.0, 2018). It incorporates technologies such as field buses, which enable interoperability and data exchange between different hardware and software components (Sino-German Industrie 4.0, 2018). The asset layer describes reality and represents the physical components (Sino-German Industrie 4.0, 2018).

Asset Life Cycle

The "Life Cycle & Value Stream" axis illustrates the life cycle of assets based on IEC 62890, 2020 *Industrial-process measurement, control and automation - Life-cycle-management for systems and components*. There is a differentiation between type and instance assets, where the type represents a design and prototype and an instance represents the actual product (Hankel and Rexroth, 2015). The axis encompasses the asset value stream from the development of a type asset to the maintenance and usage of an instance asset. IEC PAS 63088, 2017 states that the axis describes the asset state at a particular location and point in time from production to disposal.

Hierarchy

The "Hierarchy Levels" axis consists of the seven levels: product, field device, control device, station, work centres, enterprise and connected world. Within a facility, each of these levels represent a function (Hankel and Rexroth, 2015). The allocation of functional models to hierarchy levels is adapted for the needs of Industry 4.0. It is based on the reference architecture model for a factory and IEC 62264-1, 2013 *Enterprise-control system integration - Part 1: Models and terminology*.

3.2 Maintenance Planning

EN 13306, 2017 provides a definition of maintenance as a comprehensive blend of technical, administrative, and managerial activities throughout the lifespan of an item, aimed at preserving or reinstating its ability to fulfil its intended purpose. Various maintenance strategies are available to accomplish the objectives of maintenance. Figure 3.2 presents a method of classifying these strategies, with the degree of technological effectiveness progressively increasing from left to right.

Table 3.1: Architecture Layers

Layer	Definition from IEC PAS 63088, 2017	Gas detection SIF example
Business	Describes the commercial view, including organisational and regulatory conditions.	SIF ensures safety and regulation compliance, covering SIL follow-up and reporting to RNNP.
Functional	Describes functions of an asset with regard to its role in the Industry 4.0 system.	Gas detector monitors gas in air concentration. F&G logic generates alarm signals, including diagnostics, and transmits action signals in accordance with the safety strategy.
Information	Describes the data that is used, generated or modified by the asset functionality.	F&G logic generates alarm signals based on detector functionality, and action signals based on detector output and determined rules.
Communication	Describes which data is used, where it is used and when it is distributed.	F&G logic transmits alarm and action signals.
Integration	Represents the transition from the physical world to the information world.	F&G logic transforms 4-20mA signal from the gas detector to digital signals.
Asset	Represents the asset that actually exists in the physical world.	Gas detector and F&G logic with input and output.

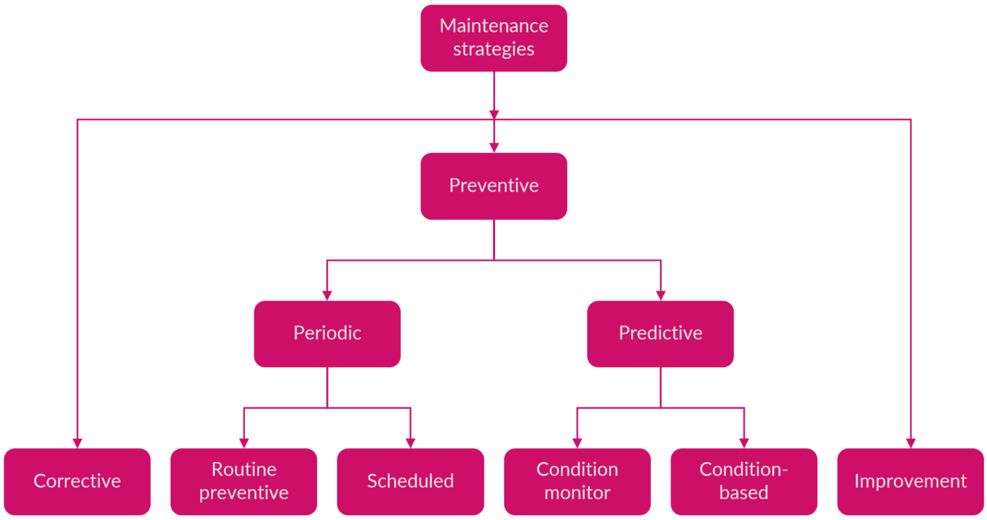

Figure 3.2: Maintenance strategies, adapted from Sahli et al., 2021 and EN 13306, 2017.

3.2.1 Corrective Maintenance

Corrective maintenance refers to maintenance activities that are performed after the recognition of a fault or failure in order to restore an item or system to its required functional state (EN 13306, 2017). It is also known as reactive maintenance, breakdown maintenance or run-to-failure. This strategy aims to address the specific issue that caused the malfunction and bring the item back to normal working conditions. One instance involves performing maintenance on a gas detector subsequent to receiving an alarm indicating beam block failure. This strategy is typically associated with high downtime, unexpected failures, reactive response to issues and high maintenance costs.

Deferred corrective maintenance is a type of corrective maintenance that is not executed immediately after a fault is detected. Instead, it is intentionally delayed according to predetermined rules or guidelines (EN 13306, 2017). The purpose of deferring the maintenance is typically to optimise resources, prioritise other tasks, or minimise disruptions to operations. The decision to delay the corrective maintenance is based on an assessment of the consequences, risks, and available resources. Deferring the corrective maintenance can save maintenance costs, but it entails higher downtime. This is often not an option for safety critical equipment.

Deferred corrective maintenance can also be opportunistic maintenance. This refers to maintenance activities that are performed opportunistically. Unlike scheduled maintenance, opportunistic maintenance does not follow a predetermined schedule or occur concurrently with other maintenance actions or specific events (EN 13306, 2017). Instead, it is typically carried out when an opportunity arises, such as when equipment or systems are already accessible or when other maintenance tasks are being performed.

Immediate corrective maintenance refers to corrective maintenance that is carried out without any delay immediately after a fault or failure is detected. The objective of immediate corrective maintenance is to prevent or minimise any unacceptable consequences that may arise due to the fault (EN 13306, 2017). It aims to address the issue promptly to avoid further damage, safety risks, or disruptions to operations.

3.2.2 Preventive Maintenance

Preventive maintenance refers to the maintenance activities performed to evaluate and address potential degradation or deterioration of an item, with the aim of reducing the likelihood of failure (EN 13306, 2017). It involves taking proactive measures to keep equipment and systems in good working condition and prevent unexpected breakdowns or malfunctions. Preventive maintenance can be broadly categorised into the two main types periodic maintenance and predictive maintenance (Sahli et al., 2021).

Periodic Maintenance

Routine preventive maintenance refers to the regular, recurring maintenance tasks that are performed on a routine basis. These tasks are typically simple and can be easily scheduled and performed by maintenance personnel. The routine maintenance can also be opportunistic maintenance (EN 13306, 2017). Routine maintenance activities often include tasks such as cleaning, lubrication, inspection, and minor adjustments. The purpose of routine maintenance is to keep the equipment in good operating condition, prevent the accumulation of dirt or debris, and identify any potential issues early on.

Scheduled preventive maintenance, also known as planned preventive maintenance, refers to maintenance activities that are performed based on a specified time schedule or a specified number of units of use (EN 13306, 2017). It involves following a predetermined maintenance plan or schedule to ensure that maintenance tasks are executed at regular intervals. Unlike routine maintenance, scheduled maintenance tasks are more comprehensive and may require more time, resources, and expertise. In scheduled maintenance, the intervals for maintenance activities are determined in advance and outlined in a maintenance plan. The tasks are typically based on factors such as equipment manufacturer recommendations, industry best practices, regulatory requirements, and historical data. This is the case for the periodic proof tests for SIS. The purpose of scheduled maintenance is to proactively address potential issues, prevent failures, and ensure the continued performance and reliability of the equipment.

Predictive Maintenance

Predictive maintenance is a process by which it can be predicted when equipment or machinery is likely to fail, allowing for taking preventive action before a breakdown occurs. Predictive maintenance can help organisations save money by reducing unplanned downtime, improving safety, and extending the life of equipment. In order to predict when equipment is likely to fail, large amount of data about the equipment in question must be collected and analysed.

Condition monitoring is an activity that involves measuring the characteristics and parameters of an item's physical state at predetermined intervals (EN 13306, 2017). It can be performed either manually or automatically. The main objective of condition monitoring is to assess any changes in the measured parameters over time, this is how it is distinguished from inspection (EN 13306, 2017). It focuses on monitoring the condition and performance of the item to detect any deviations or anomalies that may indicate potential issues or deterioration. By tracking the changes in these parameters, maintenance personnel can gain insights into the equipment's health and make informed decisions regarding maintenance actions.

Condition monitoring can be performed continuously, meaning that data is collected and analysed in real-time, providing immediate feedback on the equipment's condition (EN 13306, 2017). It can also be conducted over specific time intervals, where measurements are taken at predetermined time points to track changes in the item's condition. Additionally, monitoring can be triggered after a certain number of operations, such as a set number of cycles or hours of operation (EN 13306, 2017).

Typically, condition monitoring is carried out while the item is in its operating state, as this allows for the assessment of parameters under actual working conditions (EN 13306, 2017). This approach provides a more accurate representation of the equipment's condition and enables proactive maintenance actions based on real-time data. These actions are condition-based maintenance (CMB), which utilises condition monitoring.

CMB is a type of preventive maintenance that involves assessing the physical condition of an item, analysing the data collected, and determining the necessary maintenance actions based on the assessment (EN 13306, 2017). CMB takes into account the actual physical condition of the equipment to determine when maintenance actions are needed. The condition assessment can be conducted according to a predetermined schedule, on request when specific issues arise, or continuously through real-time monitoring (EN 13306, 2017).

The data collected from the condition assessment and monitoring activities are analysed to identify trends, anomalies, or critical thresholds that may require maintenance intervention. Based on the analysis results, predictive models that can be used to predict when equipment is likely to fail and maintenance actions can be planned and executed, such as repairs, component replacements, lubrication, or adjustments. These models can take into account a wide range of factors, including historical data about similar equipment, environmental factors, and real-time sensor data.

3.2.3 Improvement Maintenance

Modification or improvement maintenance involves making changes or upgrades to an item to incorporate technological advances or to meet new or changed requirements (EN 13306, 2017). This type of maintenance is focused on enhancing the functionality, performance, or capabilities of the equipment or system in response to evolving needs or advancements in technology. It entails assessing the current state of the item, identifying areas that can be upgraded or modified, and implementing changes to align with the latest technological advancements.

Chapter 4

Aker BP and Smart Maintenance

4.1 Aker BP Assets

Aker BP is the operator of six fields on the Norwegian continental shelf (Aker BP, 2023c). The fields include the three facilities Edvard Grieg, Ivar Aasen and Ula, the facilities connected to the Valhall area, as well as the two floating production storage and offloading (FPSO) units: Alvheim and Skarv. The company also operates some of the connected producing fields, for example Tambar, which is connected to the Ula field.

The six fields are considered assets according to the definition from Plattform Industrie 4.0, 2023a, since they have a value to Aker BP. Aker BP, 2023a gives two definitions of asset. Firstly, Aker BP, 2023a defines asset as "Aker BP's ownership share in a licence or group of licences operated or non-operated where Aker BP is fully accountable and liable". This agrees with how the term asset is used in Aker BP. In Aker BP, the six fields are referred to as assets, while other resources and equipment are not. Secondly, Aker BP, 2023a defines asset as "functional equipment or logical groups of equipment", as well as a "digital representation of physical objects or groups of objects". This definition is consistent with the definition from Plattform Industrie 4.0, 2023a, and the thesis will therefore apply this definition while using facility for Aker BP's operated fields.

Aker BP was established in 2016 through the merger of Det norske oljeselskap ASA and BP Norge AS. Over time, additional companies have joined Aker BP, resulting in a diverse range of systems and vendors being involved across their various facilities. This has led to multiple approaches and practices in different aspects of their operations. One such area is the labelling of similar equipment, where different rules and syntax are employed across different facilities. To illustrate this diversity, Aker BP utilises control systems from four distinct vendors, namely ABB, Honeywell, Kongsberg, and Siemens, within their facilities. Each vendor has their own specifications and guidelines for labelling and identifying equipment within their respective control systems.

According to EN ISO 10418, 2019, which is a standard for the management of process safety systems for offshore production installations, the use of a system for identifying and symbolising process components and process safety devices is required. Tags are used as a means to describe and uniquely identify individual equipment. They provide a unique code that defines the Functional Location (FLOC) and function of a physical component within a facility (Aker BP, 2023a). The term "functional location" refers to the specific location of the tag within the system, such as a particular unit or area, rather than the precise physical position within the facility (Aker BP, 2023a). FLOC is also used as a name for the tag or code that describes the functional location. Tag or FLOC is typically used to track and manage equipment throughout its life cycle, including design documents, maintenance, and repair activities. They help ensure that equipment is properly identified, and information about its function and location is easily accessible. This identification system aids in organising and maintaining the integrity of the facility's equipment inventory. In addition to equipment, facilities and platforms have tags which consist of a three letter code.

For Ula, the format of the tag used to indicate a line gas detector receiver involves the terms gas detector line (GDL) and receiver (R). The tag follows the pattern of *fire detection area*-GDL-*four digit number*-R. For instance, an example tag would be A2-GDL-4230-R, where A2 represents a predetermined fire area. In order to locate all line gas detectors on Ula, one can simply search for tags that include GDL and filter them out. However, it's important to note that this approach won't be effective for other facilities as they utilise different syntax structures.

To establish uniformity in equipment categorisation across facilities, Aker BP has implemented the utilisation of catalog profiles and object types. These concepts are derived from the equipment class and equipment type, respectively, as defined in EN ISO 14224, 2016. Each piece of equipment within a functional location is associated with a catalog profile, which outlines specific characteristics relevant to the failure data pertaining to that equipment type (Aker BP, 2023a). The object type serves as a subset of the catalog profile, taking into consideration additional factors such as the equipment's function (Aker BP, 2023a). For instance, the fire and gas detector catalog profile encompasses 14 distinct object types, as outlined in Table 4.1, indicating different variations of fire and gas detectors. This categorisation enables the efficient identification of all gas line detectors, such as the gas line detector IR and gas line detector laser, across all Aker BP facilities.

Aker BP's pursuit of data-driven decisions aligns with their broader objectives. Data-driven decision-making involves the systematic utilisation of data analysis and interpretation to inform and guide the decision-making process. It entails leveraging data to enhance the accuracy and effectiveness of decision-making. In the modern era, the exponential growth in available data and advancements in data collection and analysis technologies have heightened the significance of data-driven decision-making for organisations.

Aker BP collaborates with suppliers to foster the development of new technologies and innovative approaches, all based on shared data (Aker BP, 2023d). They place emphasis on establishing safe and secure methods that enable them to tackle numerous tasks from shore. By implementing a systematic categorisa-

Table 4.1: Object type of fire and gas detectors.

Object Type	Object Type Description
FG	Fire/Gas detectors
FG-CP	LOGIC SOLVERS AND CO
FG-FD	FLAME DETECTOR
FG-FDV	FLAME DETECTOR VIDEO
FG-GD	GAS DETECTOR MISC
FG-GDACO	GAS DET. ACOUSTIC
FG-GDCAT	GAS DET. CATALYTIC
FG-GDLOSIR	GAS LINE DETECTOR IR
FG-GDLOSLA	GAS LINE DET. LASER
FG-GDPIR	GAS POINT DET. IR
FG-HD	HEAT DETECTOR
FG-OMD	OIL MIST DETECTOR
FG-PGD	PORTABLE GAS DETECTOR
FG-SD	SMOKE DETECTORS

tion of equipment across their facilities, Aker BP lays a foundation for data-driven decision-making. This standardised approach allows for comprehensive data collection, analysis, and comparison, which ultimately enhances their ability to make informed decisions based on reliable data.

4.2 Predictive Maintenance at Edvard Grieg

At Edvard Grieg, statistical analysis and weather forecast is used for maintenance planning of F&G detectors (Pettersen et al., 2020). Pettersen et al., 2020 explains the steps used for implementing predictive maintenance:

1. Real-time monitoring: What is happening right now?
2. Statistical analytics: What has happened?
3. Predictive analytics: What is going to happen in the future?

Monitoring the detectors is a crucial step for gathering the data for the analytics, and also for using in the predictive analytics. The Honeywell Asset Sentinel software was used for the monitoring. For the statistical analysis, two and a half years of fault data was analysed for all F&G detectors. Honeywell Asset Sentinel was also used for the statistical analysis. The analysis resulted in identifying the physical locations where detectors were having more faults, identifying bad actors and a comparison of the fault intensity between vendors (Pettersen et al., 2020).

Predictive analytics in Honeywell Asset Sentinel was used by correlating real-time monitoring and historic events to past weather conditions (Pettersen et al., 2020). Machine learning was then used to predict future conditions for the detectors based on weather forecast data. After a 33 month supervised learning period and 12 months validation, the overall prediction accuracy achieved was $> 75\%$, including errors in the weather forecast (Pettersen et al., 2020). The model runs in real-time and the accuracy can improve by retraining the model with new data.

Chapter 5

Data Tools and Systems

5.1 Cognite Data Fusion

5.1.1 Purpose

CDF is an industrial DataOps platfrom provided by Cognite (Cognite, 2022). The CDF tools and services can be used for gaining business value from big data by building solutions and applications. Integration of data from the information technology (IT) and operational technology (OT) systems in a cloud platform like CDF is an important step towards Industry 4.0 and the benefits it brings. Data becomes more accessible when using CDF, this can be utilised for better decision-making.

IT and OT systems are the main types of source systems. IT systems are used for data and computing, an example being the resource-management system SAP presented in Section 5.3. The safety and automation system (SAS), see Section 5.4, is an example of an OT source system, which are systems used for monitoring processes and events. Monitoring is often a continuous process, requiring the data to be extracted to CDF in real-time.

Once the data from both the IT and OT systems are accessible in CDF, applications and solutions can easily be built on top of it (Cognite, 2023). Cognite InField is an example of an application running on top of CDF (Cognite, 2022). Figure 5.1 illustrates how data from SAS, SAP and Miros are integrated in CDF, making it accessible for users on different devices. These are only a few of the data sources streamed to CDF, but they are the ones of the most interest for this thesis. CDF can be an operational digital twin for assets, combining real-time data with static data about an asset.

The CDF platform facilitates for contextualisation of company data. Resources are organised, leading to a better understanding of the data, by combining machine learning and a rules engine in CDF with the company's domain knowledge (Cognite, 2022).

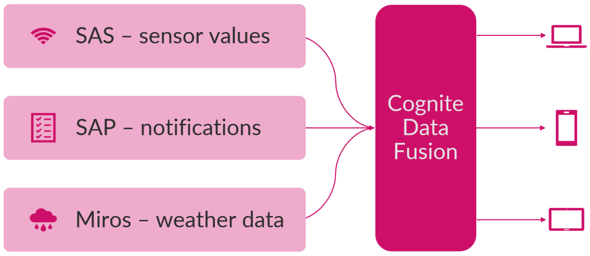

Figure 5.1: Cognite Data Fusion as a complete operational digital twin of assets, adapted from Cognite, 2023.

5.1.2 Functionality

The CDF platform architecture is shown in Figure 5.2. The modular design shows how IT and OT data are extracted and how CDF through three modules facilitate for data applications and analysis. The extractors used with CDF are not restricted, so that data from both IT and OT data sources can be integrated into CDF. As an example, OPC UA is used as the extractor for the OT data from SAS. Staging area is the first CDF module, where data is stored in its original format after being extracted from the data sources Cognite, 2022 The data is reshaped to fit the CDF data model by running transformations in the transform module. In the CDF data model, the data is enhanced. Data from different source systems can be mapped to each other by using the CDF contextualisation tools. The CDF architecture shows how CDF provides the cloud infrastructure from Figure 6.1.

Figure 5.2: The Cognite Data Fusion platform's modular design, adapted from Cognite, 2022.

There are six different resource types for storing data in the CDF data model, and three resource types for organising data. CDF stores data in the resource types "asset", "time series", "events", "files", "3D models" and "sequences"; they are described in Table 5.1. Relationships between the stored data are defined using the resource types "relationships", "labels" and "data sets", described in Table 5.2.

The CDF home page contains different tools under the following categories, as seen in Figure 5.3. There is also a separate application called Asset Data Insight for viewing the CDF data. The application is still in beta.

1. Integrate
2. Contextualise
3. Explore and build
4. Manage and configure

Table 5.1: Resource types to store data, from Cognite, 2022.

Resource Type	Resource Type Description
Asset	Digital representations of objects or groups of objects from the physical world
Time series	A series of data points in time order
Events	Information that happens over a period of time
Files	Documents that contain information related to one or more assets
3D models	Files that provide visual and geometrical data and context to assets
Sequences	Series of rows indexed by row number

Table 5.2: Resource types to organise data, from Cognite, 2022.

Resource Type	Resource Type Description
Relationships	For representing connections between resource objects in CDF
Labels	For creating predefined sets of managed terms for annotating and grouping
Data sets	For containing data objects and metadata with information about the data it contains

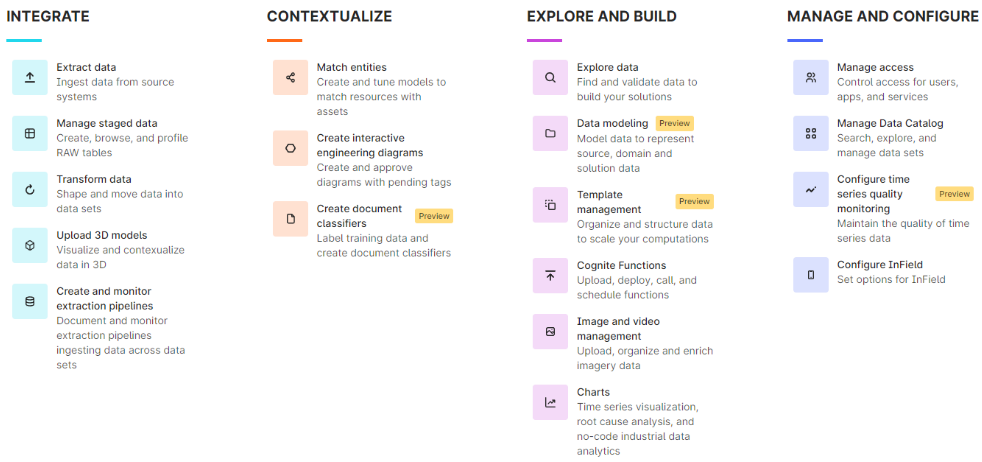

Figure 5.3: The Cognite Data Fusion home page.

5.1.3 Flexible Data Modeling

"Data modeling" is found under explore and build on the CDF home page. This modelling tool, called FDM, allows for creating data models for organising data objects with the GraphQL data modelling language (Cognite, 2022). A data model will represent data entities and their relationships by defining resource types for the entities. Fields in the data types will represent entity attributes. Relationships are defined by giving a data type a field where the attribute is a data type that is also defined in the data model.

Data can be uploaded to the staging area by using the "manage staged data" tool under integrate, as seen in the leftmost column of Figure 5.3. A data model can then be populated with this data by using "transform data", also under integrate. The query explorer can then be used for querying the data from a data model.

5.2 Aveva Net

Asset hierarchies and life cycle information (LCI) data are stored in the life cycle information (LCI) Aveva Net application. LCI refers to the comprehensive range of data and details that a company needs to effectively manage and oversee various stages of a facility's life, including engineering, ongoing operations, maintenance, repair, modification, and eventual decommissioning. LCI encompasses the necessary information and resources essential for the successful planning, execution, and decision-making throughout the entire life cycle of the facility. This is typically static information like technical data, tag data and technical documents for equipment.

5.3 SAP

SAP plant maintenance (PM) is a computerised maintenance management system (CMMS) software product. The function of SAP is to facilitate for maintenance operations. One way of doing this is through the notification and work order system.

In SAP, a data object called a notification is created during the identify and validate work process (Aker BP, 2023a). Notifications can take various types and can be associated with different work orders depending on the situation. When it comes to corrective maintenance, Malfunction report (M2) notifications play a crucial role as they are utilised when there is a functional degradation of equipment (Aker BP, 2023a). These notifications encompass failure data in line with EN ISO 14224, 2016, including failure mode, failure impact, failure description, and more. Additionally, they provide an initial priority based on a matrix that assesses the consequences of failure against the classification of the functional location referenced in the notification (Aker BP, 2023a).

Once a notification is validated, a work order is linked to the notification. This work order contains detailed information about the resources required, such as labour and materials, to restore the equipment's functionality (Aker BP, 2023a). Following the completion of the work specified in the work order, the repair report is also connected to the notification through the "Report work" process.

Functional units in SAP are labelled with Functional Location (FLOC). As explained in (SAP, 2022), FLOC represents an element of a technical structure within a system. FLOCs are distinct codes that define both the functional location and the function of a physical component within a facility. The term "functional location" specifically denotes the position of the tag within the system and not the precise physical location. According to Aker BP, 2023a, Aker BP defines functional location as equivalent to a tag. However, it is important to note that in SAP, the three-letter facility tag is incorporated as a prefix in all equipment tags associated with that particular facility. This means that in SAP, the equipment tags include both the facility tag and the functional location.

5.4 SAS

SAS refers to an integrated system that combines safety functions and automation control in an industrial installation. SAS performs multiple tasks, including monitoring, logic control, and safeguarding, to ensure the safe and efficient operation of the installation.

IEC PAS 63131, 2017 defines a set of operational control function blocks. Function blocks are a programming concept used in control systems and automation. They are modular units of code that encapsulate specific functionalities or behaviours. The function blocks help companies comply with the software requirements from IEC 61508, 2010. In addition, the control functions increase the standardisation of digital information and contributes to achieving Industry 4.0. Aker BP has different control system suppliers; the operational control functions standardise the control system application.

The Monitoring of analogue process variables - fire and gas (MA_FG) function block defines inputs and outputs for fire and gas detectors and ensures display and monitoring of the detector variables (IEC PAS 63131, 2017). It is also defined which inputs and outputs shall be accessible from a operator station. The operator station outputs include alarms and faults. An event will trigger an output in the function block, for example "dirty optics" or "beam blocked".

Open Platform Communications Unified Architecture (OPC UA) is a communication protocol and framework for industrial automation. It is designed to enable secure and reliable communication between various devices and systems in the industrial environment. OPC UA provides a standardised way for different components of a control system to exchange data and interact with each other. It supports interoperability across different platforms and vendors, making it widely adopted in the industry.

Chapter 6

Specifications

The system life cycle processes in IEC 15288, 2015 are defined in detail. Each process provides a step guide with clear goals and specific outcomes. This differs from the RAMI 4.0 layers that are part of the framework for structuring and understanding complex systems. The RAMI 4.0 layers can be used for mapping the crucial aspects of a data model, but this requires an understanding of the layers since they do not contain detailed processes. It is therefore valuable to associate life cycle processes to the RAMI 4.0 layers. The technical processes from IEC 15288, 2015 corresponds to the RAMI 4.0 layers like in Table 6.1.

The first of the technical processes in IEC 15288, 2015 is the "business or mission analysis process". The process process aim is determining potential system classes by analysing the business perspective of a problem. Hence, this process corresponds well with the commercial perspective in the "business" RAMI 4.0 layer.

The "system requirements definition process" has the purpose of defining the system functionality as well as creating measurable system requirements. The process overlaps with the "functional" RAMI 4.0 layer. However, RAMI 4.0 layers do not consider the measurable system requirements.

The "architecture definition process" aims at generating alternatives for the system architecture. This includes describing the necessary data which characterises the "information" layer from RAMI 4.0. This process also identifies the interfaces of system elements, which could be a part of both the "communication" and

Table 6.1: RAMI 4.0 layers and corresponding technical processes.

RAMI 4.0 layers	Technical processes from IEC 15288, 2015
Business	Business or mission analysis
Functional	System requirements definition
Information	Architecture definition
Communication	Architecture definition and design definition
Integration	Architecture definition and design definition
Asset	Design definition

"integration" layers.

Interfaces are also considered in the "Design definition process". This process defines design characteristics for all system elements. The purpose of the process is describing the system and its elements in sufficient detail. This process corresponds to the "communication" and "integration" layers, like the architecture process. It also provides detailed information about the assets, hence, it resembles the RAMI 4.0 "asset" layer.

6.1 Use Case Specification

6.1.1 Business Analysis

Prepare for business or mission analysis

The thesis objective of creating a data model for monitoring optical gas detectors is closely aligned with Aker BP's overall strategy of digitalization. Aker BP recognises the importance of using digital technologies to achieve their goals of reducing emissions, enhancing safety, improving efficiency, and lowering costs (Aker BP, 2023d). By creating a data model for monitoring optical gas detectors, the thesis aims to contribute to Aker BP's efforts to improve maintenance planning, which is a key aspect of their overall strategy.

Effective maintenance planning can help to reduce emissions by minimising the need for unplanned maintenance activities. It can also improve safety by ensuring that the optical gas detectors are working correctly and accurately detecting hazardous gases. Improved maintenance planning can also improve efficiency by reducing downtime and increasing equipment reliability. Finally, it can lower costs by reducing the need for expensive emergency repairs.

Define the problem or opportunity space

Weather conditions can cause dirty optics and beam block of optical gas detectors. Due to this, detector lenses are only cleaned as a reactive maintenance measure, which can be time-consuming. Maintenance work on offshore facilities is complicated as technicians need to be transported to the platform, and there are limited accommodations available. Therefore, planning for maintenance work needs to account for the required technicians and optimise the utilisation of the available human resources on the platform. This task becomes more complicated when reactive maintenance is necessary, and significant time and costs can be saved by avoiding such instances.

In the case of unmanned or low-manned platforms, the significance of avoiding detector failures is even greater as there may not be any technicians available on-site. The risk of process shutdown due to detector failures increases with the time taken to rectify the issues. In the event of a storm, multiple detectors may get blocked and fail, leading to a shutdown when there are too few gas detectors available in the area. The cost of a process shutdown is substantial, and the resulting start-up procedure can have adverse effects on the environment.

Gas detection systems are a crucial aspect of safety, and preventing failures in these systems is of utmost importance. However, detector faults triggered by weather conditions have not been analysed systematically in Aker BP. This lack of analysis means that detectors that are more susceptible to faults caused by weather may go unnoticed. To avoid failures caused by weather conditions, it is necessary to implement predictive maintenance measures.

Characterise the solution space

By implementing a data model that visualises the patterns between failures in optical gas detectors and weather conditions, several benefits can be achieved. Firstly, it can help avoid failures in critical safety systems by identifying potential issues before they cause equipment failure. Secondly, it can help identify bad actors, or specific detectors that are more susceptible to weather-based faults, allowing for more targeted maintenance efforts. Finally, by enabling more efficient use of offshore manpower resources, the data-driven approach can lead to improved efficiency and reduced costs.

By collecting and analysing data from gas and weather detectors, predictive models can be developed that enable proactive maintenance planning and scheduling, reducing downtime and increasing gas detector reliability. Data-driven decision-making also helps Aker BP make informed decisions about when and how to perform gas detector maintenance, ensuring optimal resource allocation. Through the application of digital technologies and data analytics, Aker BP can optimise its maintenance processes, resulting in improved safety, reliability, and operational efficiency. The data model will therefore be designed for integration with Aker BP's existing maintenance planning systems, enabling maintenance teams to make data-driven decisions about when and how to perform maintenance on the detectors.

6.2 Requirement Specification

6.2.1 System Requirements

Prepare for system requirements definition

Data-driven decision-making is critical to the success of predictive maintenance. To predict when equipment is likely to fail, organisations need to collect and analyse a large amount of data about the equipment in question. The solution therefore starts with the collection of the relevant data and ends with a model that predicts equipment failure.

A data model could visualise the patterns between failures on optical gas detectors and weather conditions. This can be used to anticipate expected failures and schedule maintenance activities accordingly, thus allowing for efficient cleaning of the detector lenses. To predict equipment behaviour and enable data-driven decisions, the data model must combine data from different sources. The key parameters are the historical data for weather and diagnostic alarms and fault events from the detectors. In addition, work orders and notifications are relevant for understanding past detector faults and determining their root cause.

Cyber-physical systems like this can be described using a three-level architecture. Figure 6.1 shows this architecture, where the first level is physical objects, representing the physical components like gas detectors and weather sensors. The second level of the architecture is the cloud infrastructure layer. This layer provides the computational resources and storage necessary to process and store the data generated by the physical objects. It includes servers, databases, and other cloud-based services that enable the processing and analysis of data. For this system, CDF will be used as the cloud infrastructure. The third and final level of the architecture is the services layer. This layer provides the user-facing applications and interfaces that allow users to interact with the cyber-physical system. This architecture allows for the separation of concerns between the physical components, the computational infrastructure, and the user-facing applications, which can make it easier to develop, maintain, and update these systems.

Figure 6.1: Cyber physical systems

The scope of this thesis only covers the cloud infrastructure part of the cyber-physical system needed to meet the problem solution from the business analysis. The integration of information from the physical objects to CDF is an ongoing project in Aker BP. The thesis presents the relevant data sets in CDF and a data model implemented in CDF. The function starts with the collected data already in CDF and ends with the data connected to the model for analysis. The analysis can be considered as a part of an application or service and is not performed in the thesis. It is important that the data model is well defined, so that additional value can be gained by connecting to apps and algorithms.

Define system requirements

The objective of the data model is to capture the correlation between weather conditions and the reliability of optical gas detectors. It establishes a structured framework for organising, analysing, and interpreting data pertaining to weather parameters and their impact on the availability of optical gas detection systems. To accomplish this, the data model integrates information from various sources.

The data utilised in the data model will be sourced from pre-existing data sets within CDF, guaranteeing the utilisation of reliable and validated data sources.

The FDM tool is used because it not only facilitates convenient access to the data within CDF but also empowers users to perform queries on the data model. Additionally, it enables the definition and analysis of relationships between different data elements. This is attained with the first two system requirements.

1. The data model shall be implemented with FDM.
2. The data model shall integrate data through CDF.

To retrieve fault events, the data model accesses the data generated by the gas detector MA_FG function block. Meteorological data, encompassing temperature, humidity, wind speed, and visibility, is collected from a meteorological service. Descriptive information regarding the cause of a detector fault is obtained from notifications generated by SAP. Furthermore, the data model encompasses details about the placement of gas detectors within the equipment hierarchy, including the object type and catalog profile. This allows for the extraction of entire groups of a particular equipment type, such as optical line gas detectors with the object type FG-GDLOSIR. The system requirements three to seven ensure the incorporation of essential information into the data model.

3. The data model shall structure gas detectors in the Aker BP equipment hierarchy.
4. The data model shall structure weather conditions.
5. The data model shall structure gas detector events, looking at dirty optics, beam block, and fault.
6. The data model shall structure gas detector notifications.
7. The data model shall include the object type and catalog profile for equipment.

The gas detector events and notifications encompass relevant information detailing the gas detector they are associated with. To establish a contextual relationship, the data model incorporates timestamps and geographical data for weather data and detector events. This enables the observation of these factors in relation to each other. Notifications will also include timestamps to provide temporal information. These specifications are attained by system requirements eight to eleven, maintaining the integration of timestamps and geographical data within the data model.

8. The data model shall include gas detector tag for gas detector events, and notifications.
9. The data model shall include geographical data for the gas detectors.
10. The data model shall include geographical data for the weather data.
11. The data model shall include the timestamps for weather data, gas detector events, and notifications.

The gas detector events, notifications, and corresponding object types are interconnected with the relevant gas detector within the equipment hierarchy. To establish the relationship between weather factors and gas detector faults, it is necessary to compare data from a specific location and time period. Consequently, both the gas detectors and weather data are associated with a facility. Moreover, the timestamps of the detector fault events are synchronised with the corresponding timestamps in the meteorological data. This synchronisation procedure guarantees the precise alignment of fault events and meteorological data. As a result, the fault events and their corresponding meteorological data are merged based on their synchronised timestamps. This merging process facilitates the examination of patterns, correlations, and insights regarding the connection between fault occurrences and meteorological conditions. System requirements twelve to fifteen are in place to ensure the fulfilment of these criteria.

12. The data model shall connect the gas detectors with their associated object type, gas detector events, and notifications.
13. The data model shall connect gas detectors and weather data to their associated facilities.
14. The data model shall merge gas detector fault events with corresponding weather parameters based on timestamps and geographical associations.
15. The data model shall connect notifications to gas detector events based on timestamps.

6.2.2 Architecture Definition

Prepare for architecture definition

The data model comprises the main entities gas detectors and weather data. The gas detector represents the gas detection device that utilises optical methods for sensing and measuring gas concentrations. This entity encapsulates properties such as its unique identifier, location, detector type, maintenance notifications and fault events from the MA_FG function block. The weather data represents various weather condition attributes at a specific location that might affect the lens or the line of sight of a gas detector. These attributes include temperature, humidity, wind speed, and visibility, with associated timestamps and units of measurement. These parameters serve as inputs for analysing their influence on gas detector alarms and events.

Develop models and views of the architecture

In the data model, relationships are established between the entities. A gas detector is associated with weather data through specific weather sensors based on their geographical proximity. Weather parameters are recorded and associated with a particular weather station and timestamp. The weather sensors are located on the same facility as the gas detector, and therefore measure the weather factors that affect the detector.

The gas detector events and alarms come from the MA_FG function block in the SAS. These are affected by weather factors in that the SAS measures dirty optics and beam block on the line gas detector receiver. If the weather causes poor visibility or dirty lenses, alarms and events will be generated by the MA_FG function block. The data model captures this association between weather conditions and the performance of the optical gas detector. This relationship indicates that weather conditions impact gas detection by influencing the availability of the detector.

Notifications and work orders come form SAP. Each notification is linked to a specific gas detector unit. Gas detector failure can lead to generation of notifications and work orders.

Gas detector data like events from the SAS and maintenance data form SAP are stored in CDF and connected to the relevant gas detector tags. The gas detector tag is also linked to the associated platform and facility. Weather data is likewise linked to facilities in CDF. It is not, however, linked directly to the gas detector or detector events, which is an aim of the data model.

The entities in the system architecture possess distinct characteristics and are organised with colour-coded representations based on their respective properties. The colour magenta represents physical assets, for example a gas detector. Information that is digital is coloured in orange. An example is a gas detector notification, which is a description of a failure, stored in a CMMS. Green represents phenomenons that are physical but not solid, like humidity or dirty optics. The phenomenons in the data model can all be measured. The colour-coding is demonstrated below:

- Physical asset
- Logical/digital value
- Phenomenon

This colour-coding is also applicable for the following schematics. Entities of all these characteristics are represented digitally in CDF, in accordance with RAMI 4.0. The physical assets are represented with their FLOC, functions and properties. The phenomenons are represented as time series with the measured values and corresponding timestamps as well as associated properties and assets.

Figure 6.2 is a model of the described relationships. A facility is divided into platforms, which contain gas detectors. A facility also holds weather sensors, which measure the weather factors. Fog, humidity, temperature and wind are included as weather factors. A gas detector is a part of the SAS, represented by the MA_FG function block. Dirty optics and beam block events are generated by the MA_FG function block, and the fault signal can be set accordingly. Notifications are sometimes created in SAP when a fault is observed. Weather factors, dirty optics and beam block are elliptical to point out that this is the focal point of the architecture.

6.2.3 Design Definition

Prepare for design definition

The data model is implemented with FDM within CDF, which is the industrial data platform used by Aker BP to provide accessibility to all their data (Aker BP, 2023d). This platform enables the creation of models, development of applica-

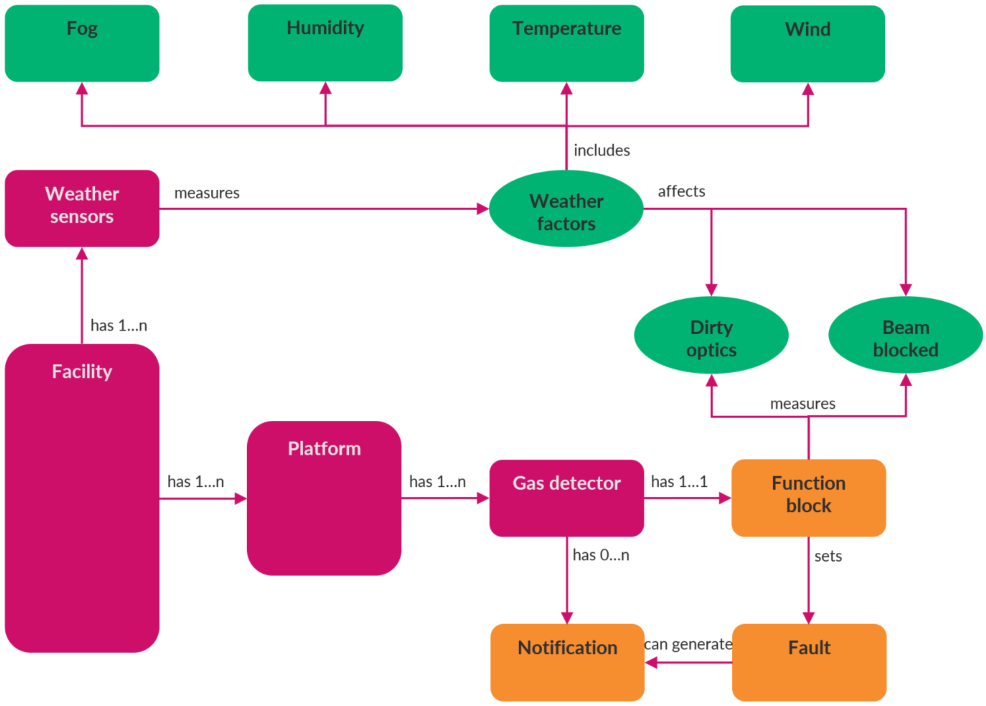

Figure 6.2: Architecture of weather effects on gas detectors

tions, and analysis based on the available data. Within CDF, information regarding each system element that constitutes the overall system is stored, eliminating the need for additional technologies to construct the data model.

Establish design characteristics and design enablers related to each system element

The data model design consists of the entities and their associated attributes listed in Table 6.2. They are also illustrated in Figure 6.3. A lot of information is stored in CDF and many attributes could be added. Those that are included are meant as the minimum for describing the necessary data and relationships according to the system requirements and business analysis. The gas detector ID, or tag, is a unique identifier for the detector. The platform states the detector location, and the object type is necessary for distinguishing between different detector types and filtering out IR line gas detectors, which are most prone to fail due to the weather. The facility is the link for connecting the correct weather data to the detectors, while the function block entity contains the alarms and events that it is desirable to see in accordance with the weather factors. The notifications connected to the gas detector can help determine the cause of detector failures.

The use of object types for IR line gas detectors serves the purpose of distinguishing these detectors from other types of detectors. This differentiation allows for the specific loading of IR line gas detector objects from the Aveva Net hier-

Table 6.2: Data model entities and their associated attributes.

Entity	Attributes
Gas detector	ID, description, platform, object type
Platform	ID, facility
Facility	ID
Weather factors	type, description, unit, facility, measurements
Catalog profile	ID, description
Object type	ID, description, catalog profile
function block	gas detector, dirty optics, beam blocked, fault
Notification	gas detector, description, failure mode, start time, long text

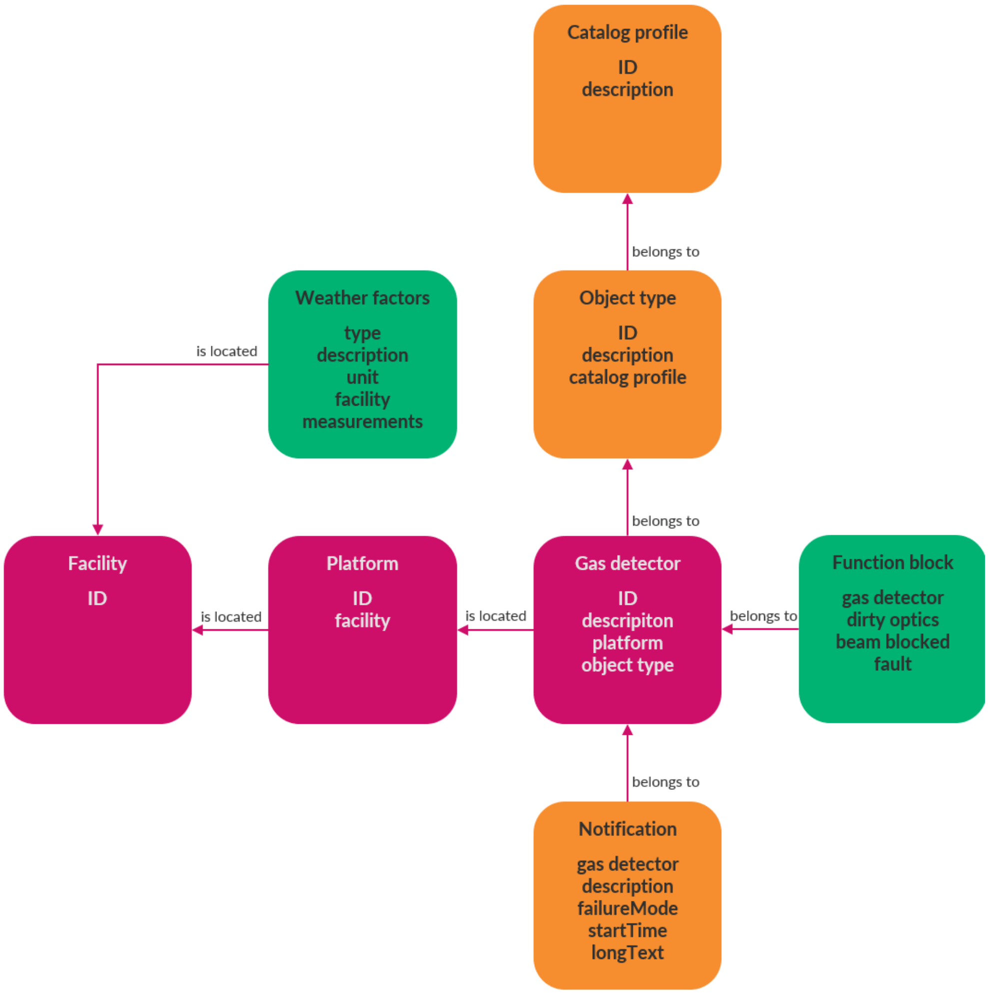

Figure 6.3: Design of weather effects on gas detectors data model.

archy into the data model in CDF. By doing so, it becomes possible to include all the detectors without the need to manually process each tag individually, especially considering that tag syntax may vary across different facilities.

By extracting the corresponding platform and facility information from the gas detector objects in the Aveva Net hierarchy, it becomes feasible to connect weather factor measurements to the respective facilities. This enables the loading of specified weather factors associated with a facility into the data model.

In the context of SAP, object types are also utilised. Leveraging this, it becomes possible to assemble all notifications that pertain to IR line gas detectors. These notifications can then be linked to their respective gas detectors through the use of tags. To accomplish this, the facility code must be employed since it is included as part of the detector's FLOC in SAP.

Regarding function blocks from the SAS, they are not categorised with catalog profiles and object types. Nevertheless, they are connected to the tags derived from the Aveva Net asset hierarchy. Therefore, when loading the IR line gas detectors from Aveva Net using the object types, the function blocks can be loaded by utilising the compiled list of tags.

Chapter 7

Implementation in CDF

7.1 CDF Projects

Aker BP uses three main projects for organising their data in CDF. This facilitates for a structured data flow. Each project serves a distinct function in ensuring data quality throughout the data flow process. The first project is "akerbp-dev". This project serves as a development environment for creating and refining data sets. Data engineers and analysts can work within this project to build and enhance data sets. It allows for experimentation, prototyping, and iterative development of data before it is considered for further stages. When uploading data sets to CDF, different application programming interface (API)s are used depending on the data source. APIs provide a set of protocols, rules, and tools that define how to interact with different source systems and access their data.

The next project is the "akerbp-test" project, which is dedicated to quality testing. Once data sets are developed in "akerbp-dev", they are moved to this project for quality assurance processes. Quality testing could involve various validation checks, data integrity assessments, and verification of data accuracy to ensure it meets predefined standards.

The final project, the "akerbp" project, is designed for production use, containing updated and live data. Once data sets successfully pass quality testing in the "akerbp"-test project, they are then moved to the "akerbp" project for deployment in a production environment. This project is intended to host the finalised, high-quality data sets that are utilised for day-to-day operations, analytics, and decision-making within Aker BP.

Organising data into distinct projects within CDF enables Aker BP to establish a well-defined data flow process from development to quality testing to production. This structured approach is crucial, particularly during the initial phase of implementing CDF when integrating data from various sources for the first time.

In the upcoming section, the relevant data sets for the data model will be explored, focusing on the Ula facility and specifically the gas detector with tag number A2-GDL-4230-R. This gas detector is situated in a weather-exposed area on the ULP. The integration progress of the Ula and Valhall facilities into CDF has come the furthest.

7.2 Data Sets in CDF

7.2.1 Asset Hierarchy

The asset hierarchies from Aveva Net serve as the primary source for all assets and tags at Aker BP (Aker BP, 2020). The Aveva Net asset data is accessible through the PostProcessor (PP) API, and it seamlessly integrates into the CDF data model as asset objects. Within CDF the hierarchical structure that forms the core of the data model refers to all objects as assets or asset objects. The top-level asset in this hierarchy is known as the "root asset". However, it's important to understand that in the context of Aker BP, the term "assets" typically specifically refers to root assets. Conversely, the term "tags" is used to describe equipment or objects that exist below the root node in the hierarchy. In CDF, the asset hierarchy data is managed under the data set named "Aveva Net, asset hierarchy". Figure 7.1 shows the CDF view of the root asset ULA, and its direct children assets. The parent asset represents the facility Ula and the children assets represent the platforms ULP, Ula living quarters platform (ULQ) and Ula drilling platform (ULD). Figure 7.2 illustrates the same hierarchy in a general manner. Facilities are structured as the root assets, with platforms and equipment as assets belonging to a facility.

Name	Dataset
^ ULA	Aveva Net, asset hierarchy
⌄ ULP	Aveva Net, asset hierarchy
⌄ ULQ	Aveva Net, asset hierarchy
⌄ ULD	Aveva Net, asset hierarchy

Figure 7.1: Asset hierarchy in CDF.

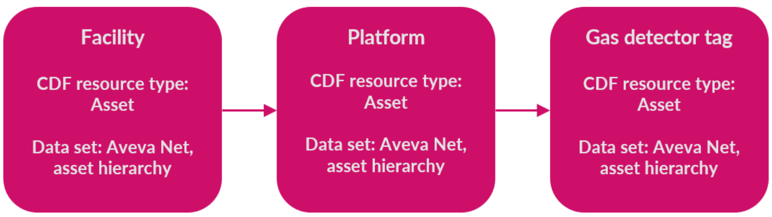

Figure 7.2: "Aveva Net, asset hierarchy".

The LCI Aveva Net app encompasses static information about the elements in the asset and tag hierarchies. This information is transferred to the asset objects

Table 7.1: Excerpt from gas detector asset object in the data set "Aveva Net, asset hierarchy".

Key	Value
objectId	A2-GDL-4230-R
External ID	ULA-A2-GDL-4230-R
PARENT TAG	FJ-05292-E
SERVICE DESCRIPTION	P02 CELLAR DECK NORTH/EAST
HAZARDOUS AREA RATING	ZONE 1
LOCATION (FACILITY AREA CODE)	P02
SAP OBJECT TYPE	FG-GDLOSIR
SAP CATALOG PROFILE	FG0000001
Data set	Aveva Net, asset hierarchy

in CDF. In CDF, the *objectId* corresponds to the tag name, which is unique per root asset (Aker BP, 2020). It is possible for tags under different root assets to have the same tag name or *objectId*, although this occurrence is rare.

To ensure uniqueness across all assets, the *External ID* for the CDF asset objects is set as "ASSET_{*objectId*}" (Aker BP, 2020). For example, the tag A2-GDL-4230-R is located under the root asset ULA, its *External ID* is “ULP-A2-GDL-4230-R”. The *External ID* serves as a unique identifier within CDF.

Using the *objectId*, the *PARENT TAG* attribute provides a reference to the parent tag for a specific tag within the hierarchy (Aker BP, 2020). The asset metadata in CDF does not explicitly list the children assets. Instead, the information about children assets is derived from the parent tags of the corresponding child nodes in the hierarchy.

According to Aker BP, 2020, various attributes and descriptions exist for different purposes within the asset and tag hierarchies. The *SERVICE DESCRIPTION* attribute is specifically pushed as the description attribute in the asset object within CDF. Additionally, all fields associated with the elements in the hierarchy, including the attributes and descriptions, are attached as metadata to the asset object within CDF.

Table 7.1 provides some of the properties from the CDF asset object that represents the A2-GDL-4230-R gas detector. Although the gas detector is located under ULP, ULP is not the direct parent tag since it is positioned several nodes higher in the hierarchy. The object type of the asset is significant as it facilitates the identification of all equipment belonging to the same type, such as all IR line gas detectors.

The *SERVICE DESCRIPTION* provides information about the location of the detector and its exposure to weather conditions. While the location is also mentioned in the *LOCATION* attribute, it may not provide sufficient details to determine the level of weather exposure. Therefore, referring to the service description is important in understanding the extent to which the detector is exposed to the weather.

According to (Emerson Automation Solutions, 2019), the *HAZARDOUS AREA RATING* indicates the probability of the gas being present in quantities sufficient to create explosive or ignitable mixtures. "Zone 1" signifies that there is a high likelihood of ignitable concentrations of flammable gases or vapours occurring under normal operating conditions. This information helps in assessing the potential risks and taking appropriate safety measures in the designated area.

7.2.2 Maintenance System Data

Aker BP's Azure API management (APIM) has been used to extract SAP data and create a data set that contains this information (Aker BP, 2023b). This is done as a part of the ongoing E2E Maintenance project. The liberated data from SAP is stored in the data set called "APIM - SAP". The "APIM - SAP" data set will replace other data sets with SAP data that exist in CDF. This data set should therefore be used over other data sets that also contain SAP data.

FLOCs from SAP include the platform code, like ULP-A2-GDL-4230-R. A FLOC object is of the CDF resource type "asset" and associated notifications and work orders are connected as shown in Figure 7.4. Notification and work order objects are of the resource type "event". The FLOC objects stored in "APIM - SAP" are contextualised to the corresponding assets in the Aveva Asset Hierarchy, as illustrated by Figure 7.3 (Aker BP, 2023b). The FLOC is used as the *Name* of an asset object from "APIM - SAP". The FLOC is also used for the metadata attribute *flocFunctionalLocation* and in the *External ID*, which is sap_apim_floc_*flocFunctionalLocation*. Other metadata attributes include *flocCatalogProfile* and *flocObjectType*.

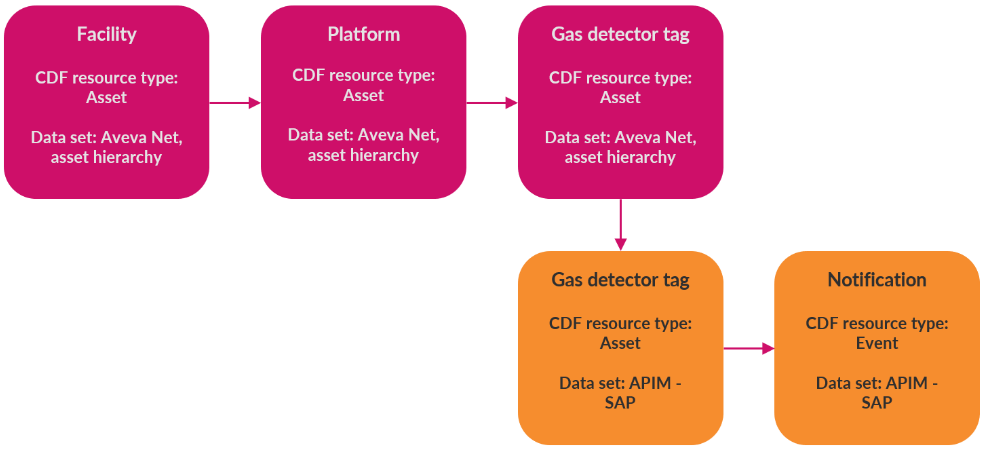

Figure 7.3: "APIM - SAP".

Figure 7.4 shows that work orders and notifications are connected. A work process is identified and validated through a notification (Aker BP, 2023b). All the data related to the equipment failure is stored in the notification. While the work order specifies the required resources in terms of work and materials necessary to restore the equipment's function, and is linked to the corresponding notification. When classifying if a gas detector failure was affected by weather factors the failure data stored in notifications is of higher value than the resource information from the work orders.

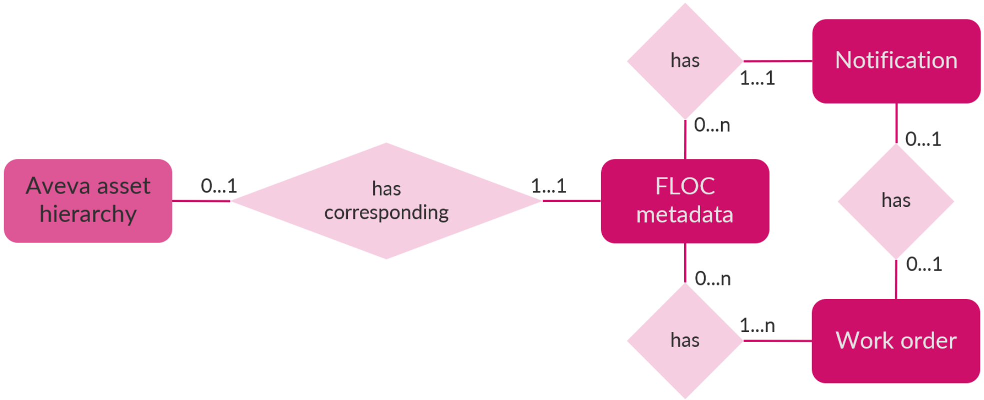

Figure 7.4: SAP data relationship diagram, adapted from Aker BP, 2023b.

Notification objects are identified using a number code stored in the attribute *notNotification* in the metadata of the notification object. The *External ID* for the notification objects is "sap_apim_notification_{notNotification}", where the unique attribute *notNotification* is inserted for each object. Notification objects also contain other fields like *notNotificationType*, *notNotificationDesc*, *mainFunctionalLocation* and *notEquipment*. The failure data is stored in the attribute *notLongText*. The information captured encompasses the date, operator name, and responses to a set of inquiries. These inquiries involve identifying the observed fault, assessing the associated risk, and determining potential reasons for the occurrence.

Table 7.2 shows some of the values from a CDF event describing a notification associated to the A2-GDL-4230-R gas detector. The linked asset is the asset object "ULP-A2-GDL-4230-R" from the data set "APIM - SAP", which is linked to the "A2-GDL-4230-R" asset object from "Aveva Net, asset hierarchy". Note that only a part of the *notLongText* value is included in this table.

In addition to the *notLongText*, the *notFailureMode* and *notFailureModeCode* provide descriptions of failures and can be utilized to determine if they are caused by weather factors. According to IEC 61511, 2017, a failure mode refers to the specific manner in which a failure occurs. For instance, in the case of dirty optics or beam block, the *notFailureModeCode* will indicate low output (LOO). This code is also applicable to other failures identified through detector diagnostics. The *notFailureEffect* also serves as a classification for the type of notification.

The notifications that specifically concern the detector's field of vision are important and cannot be filtered without analysing the free text in the *Description* field. However, numerous irrelevant notifications can be effectively filtered out by implementing the criteria of *notFailureModeCode* = "LOO" and *notFailureEffect* = "2-Degraded failure". These conditions help narrow down the notifications to

Table 7.2: Excerpt from dirty optics notification event in the data set "APIM - SAP".

Key	Value
Type	notification
Description	detector has dirty optics fault
External ID	sap_apim_notification_400111938
Linked asset(s)	ULP-A2-GDL-4230-R
Sub type	M2
Data set	APIM - SAP
notFailureEffect	2-Degraded failure
notFailureMode	LOO-Low output
notFailureModeCode	LOO
notNotificationTypeDesc	M2-Corrective Notif
notNotificationPriority	2
notNotificationPriorityDesc	2-H-High
notLongText	1. Which error is observed? Detector has Dirty Optics error
notMainAsset	Ula

those that are associated with the specified failure mode code and degraded failure classification, thereby reducing the number of irrelevant notifications.

7.2.3 Control System Data

Aker BP is currently investigating ways to transmit data to the mainland. They have established an OPC UA server that contains data from Valhall and Ula (Aker BP, 2021b). This data includes object hierarchies representing plant equipment and equipment instrumentation. The equipment objects are implemented as "asset" types in CDF and the sensor data as "time series" and "data points". Alarms and events are implemented as the type "event". According to Aker BP, 2021b, Aker BP has chosen OPC UA as their preferred communication protocol for various data integrations, highlighting the significance of stable and reliable data pipelines to CDF. Currently, there is no existing solution for handling complete OPC UA data streams. The primary method of accessing time series data presently is through PI (Aker BP, 2021b). However, in the long term, the OPC UA data stream will be used as a live stream from the SAS on all facilities.

Per now, OPC UA alarms and events from Valhall and Ula are being fed into CDF using a proprietary ABB Ability interface (Aker BP, 2021b). The SAS data is stored in the data sets "OPC UA data ULA" and "OPC UA data VAL". This data from the ABB Ability interface is the only OPC UA data available in the "akerbp" CDF project. However, "OPC UA HUB" data sets have been established for five of the six Aker BP facilities in the "akerbp-dev" and "akerbp-test" projects.

In the context of CDF, OPC UA objects representing equipment are brought in as assets. These assets are then associated with their corresponding assets in the Aveva Net hierarchy. This is illustrated by Figure 7.5. Connecting OPC UA assets to Aveva Net assets via exact matching is not reliably possible, as stated by Aker BP, 2021b. Therefore, the linking of these assets is achieved through various methods, primarily by comparing the names of the OPC UA assets with the names of the Aveva Net assets. Prior to extracting OPC UA data to CDF, time series and events are connected to the OPC UA objects. Contextualising the OPC UA data to the Aveva Net hierarchy is particularly important because SAS does not opearte with object types and catalog profiles, and are therefore not possible to filter across the facilities without this link.

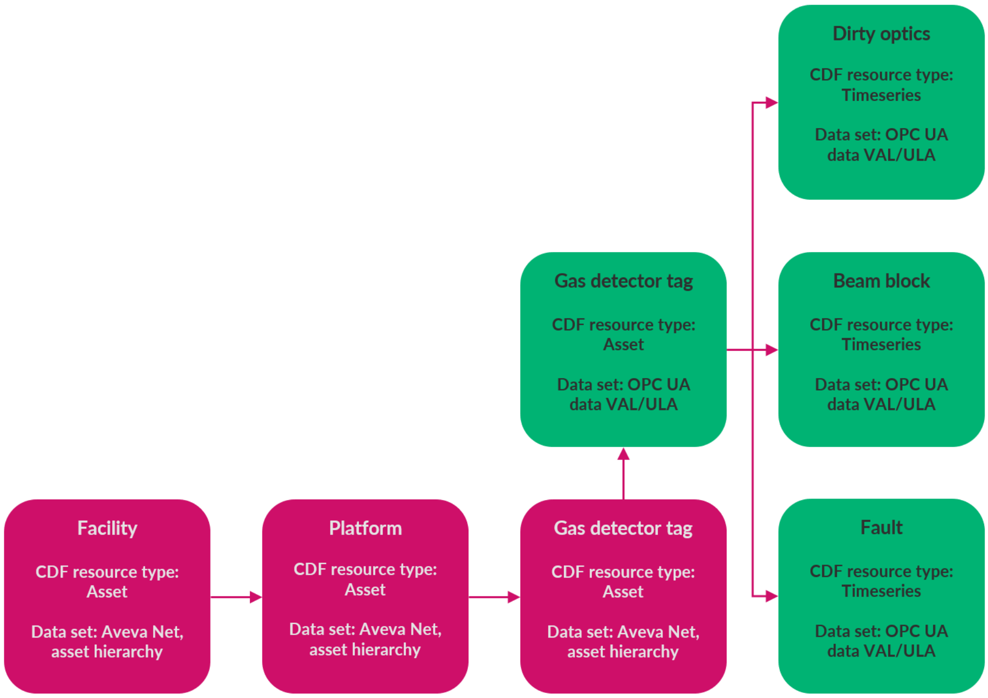

Figure 7.5: "OPC UA data".

Only the receiver component of line gas detectors has an OPC UA object. These receiver assets consist of 13 time series that represent selected measurements from the function block. Additionally, these assets include an unlimited number of events. Fault, dirty optics, and beam block are among the included time series. Table 7.3 provides the names of these time series, and the ABB names are mentioned because ABB supplies the control systems for Ula. In CDF, the specific time series are named as "Linked asset:time series name". For example, A2-GDL-4230-R:HSI.BeamBlocked. The addition of human system interface (HSI) indicates that the value corresponds to the function block inputs and outputs between an operator station. The naming conventions may differ among vendors, but they are all mapped to the same terms in CDF.

The fault, dirty optics, and beam blocked values for line gas detectors are all

Table 7.3: Function block time series naming.

Function block name from ABB	Time series name in CDF	Description from ABB
YF	YF	OUT Fault.
BFDO	HSI.DirtyOptics	OUT Dirty optics status.
BFBB	HSI.BeamBlocked	OUT Beam blocked status.

Table 7.4: Excerpt from the beam block time series in the data set "OPC UA data ULA".

Key	Value
Name	A2-GDL-4230-R:HSI.BeamBlocked
Type	timeseries
Linked asset(s)	A2-GDL-4230-R
Data set	OPC UA data ULA
dataType	Boolean

represented as Boolean values. When the "YF" variable is set to a high value, it indicates a detector fault. Similarly, a logical high value for "HSI.DirtyOptics" or "HSI.BeamBlocked" indicates that the detector has dirty optics or is beam blocked, respectively. Beam block is considered a detector fault and triggers the "YF" variable. On the other hand, dirty optics do not trigger the "YF" variable as the detectors remain operational, as stated by Håbrekke and Onshus, 2017.

The values from the "HSI.BeamBlocked" time series for the A2-GDL-4230-R detector is shown in Figure 7.6. Even though the *dataType* is "Boolean", it does not look like the time series in Figure 7.6 consists of Boolean values. This is because of the viewer in CDF Asset Data Insight. The chosen time frame on the x-axis in the figure is throughout 2022. In order to present the information in a comprehensible manner, Asset Data Insight displays an average of the Boolean value on the figure y-axis. If the time frame is made small enough, it is possible to distinguish every case of the detector being beam blocked. Notice that the y-axis interval is from 0 to 0.1. Hence, the detector was not continuously beam blocked, even in January when there was a peak.

The meta data associated with the time series includes the attributes listed in Table 7.4. The time series is a variable since it has changing values. The variable's meta data consists of properties, which are values close to constant. Both variables and their meta data end up as meta data of the associated asset, in this case A2-GDL-4230-R.

Figure 7.7 shows the time series "YF", "HSI.DirtyOptics", and "HSI.BeamBlocked" for the detector A2-GDL-4230-R. The time frame on the x-axis is 27^{th} to 29^{th} of May, 2022. The y-axis is separated in three, with "YF" in red at the top of the figure, "HSI.DirtyOptics" in blue at the middle and "HSI.BeamBlocked" in yellow at the bottom. Figure 7.7 represents the time series with Boolean values, so they

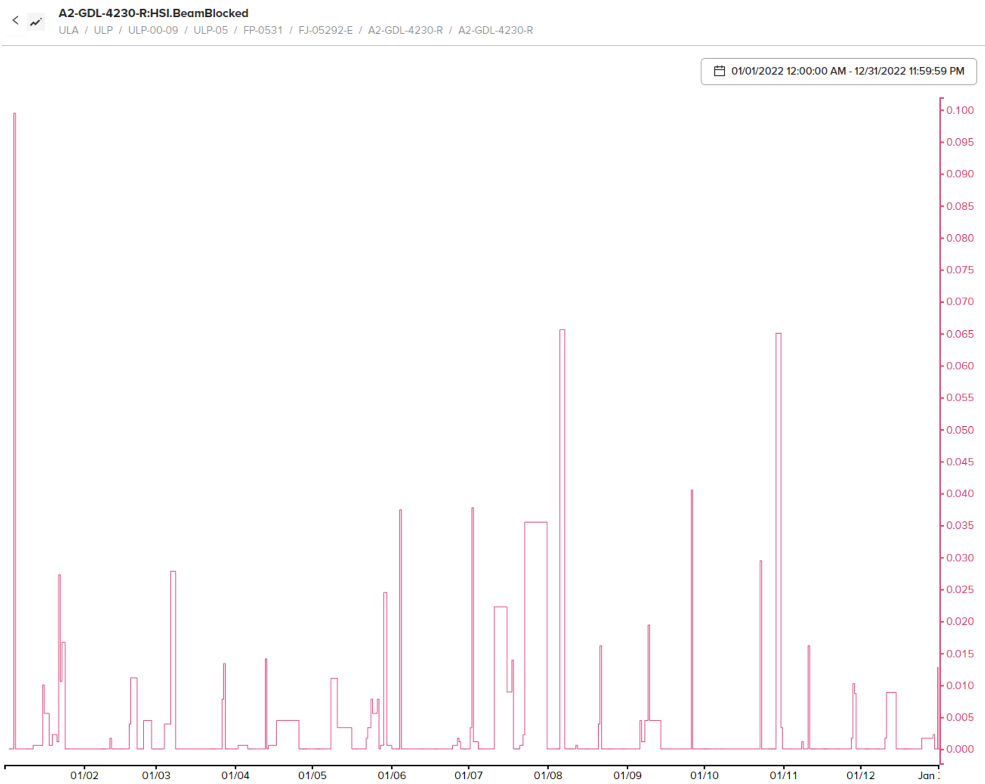

Figure 7.6: Beam block signal shown with Asset Data Insight.

are either 0 or 1. On the 28^{th} of May, the detector gets dirty optics at around 6 a.m. This persists until 9 a.m., when the gas detector is briefly beam blocked and the detector also reports a failure. Just before 5 p.m. the detector again gets dirty optics. This lasts until 9 a.m. the next day, when again, the gas detector is beam blocked and the output fault is activated. Following this the beam block and fault pins toggle several times until 6 p.m. on the 29^{th} of May. Some of the lines are thicker, like the beam block at 9 a.m. on the 29^{th} of May, because the variable is toggled but the time frame is too big for distinguishing each of the distinct cases of beam block. The "YF" and "HSI.BeamBlocked" time series follow each other. This is because beam block is considered a detector fault, and triggers "YF". However, the beam block is toggled more than the fault at 3 p.m. on the 29^{th} of May. This is due to suppression of the fault event. By this point, it is clear that there is a problem with the gas detector, and it is not expedient to receive numerous fault alarms. Note that other faults will also trigger "YF" and be affected by suppression of the alarm.

Beam blockage can be temporary and generate many alarms. With a passing fog for example, many detectors may be beam blocked simultaneously. If they also toggle between being beam blocked and not, a large number of alarms are generated. Because of this, Ula has configured the beam block alarms so that the

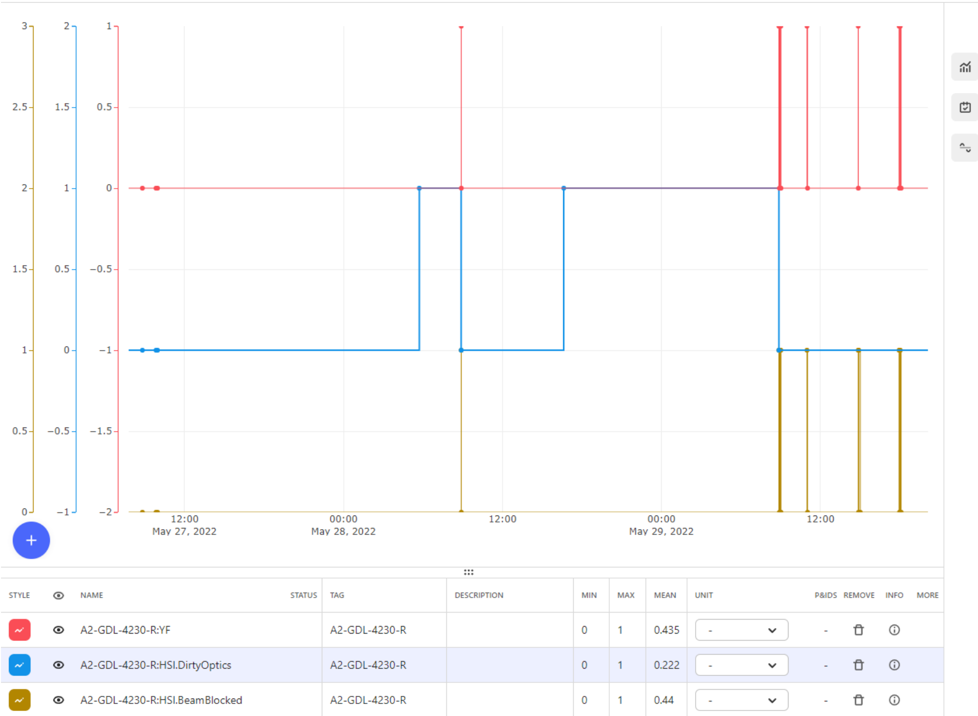

Figure 7.7: Dirty optics, beam block and fault in CDF charts.

priority increases when a detector has been beam blocked over some time. Hence, the control room is not notified about all of the beam blocked detectors.

7.2.4 Weather Data

The Norwegian Meteorological Institute (MET) conducts extensive monitoring of weather conditions on land and at sea. A significant amount of the collected data can be accessed through MET's self-service download services (MET, 2021a). MET also monitors sea areas and provides forecasts for variables such as water levels, currents, and waves (MET, 2021b). The MET weather data is available for use directly, but some of the data is also incorporated in a CDF data set. CDF contains three data sets with weather data: "StormGeo Weather Forecast," "MET Luna Weather Data," and "Miros Weather Data." However, "StormGeo Weather Forecast" has been replaced by "MET Luna Weather Data." Therefore, the relevant data sets for the data model are "MET Luna Weather Data" and "Miros Weather Data." These data sets contain measurements of various weather conditions that could affect the line of sight of a gas detector. The measurements are stored as CDF "time series."

The weather data in "MET Luna Weather Data" is extracted using the Luna API, which is used to deliver weather data to MET's commercial customers (MET, 2023). MET primarily collects information through observations, including satellite observations, and weather forecasting using numerical models and analysis (MET, 2021b). The MET data in the CDF data set are forecast data that are updated every six hours. However, if the data becomes unavailable, the historical data for that period is lost, and new forecasts are not available until the system is back online (Aker BP, 2022).

"MET Luna Weather Data" consists of 150 time series, with 25 for each facility. Out of these, ten describe factors related to the sea surface, and six describe wind factors. The remaining time series cover temperature, pressure, dew point temperature, fog, visibility, thunder, confidence, overall, and weather symbol text.

Miros is another service that provides real-time measurements of local sea state and weather conditions (Miros, 2023). It integrates sensors on-site to collect data. "Miros Weather Data" comprises over 3000 time series and is extracted using Azure (Aker BP, 2021a). This data integration was done as part of a separate project in Aker BP, which utilises the data. Aker BP is currently working on integrating weather data from all facilities, but the current documentation is limited, making it challenging to obtain a comprehensive overview of the available data. Nonetheless, it is evident that there is a substantial database.

Both the "MET Luna Weather Data" and "Miros Weather Data" data sets contain measurements of various weather conditions. The time series include measurement values, timestamps, and useful metadata such as units. "Miros Weather Data" consists of historical weather data, while "MET Luna Weather Data" provides weather forecasts. Therefore, the weather data from "Miros Weather Data" can be used for analysing detector events, while "MET Luna Weather Data" can be used for predictions based on the analysis.

7.3 Implementation in CDF

The data model was implemented using FDM. The model was created by defining data types based on the design specification. The data types were written in GraphQL code, such as the gas detector type shown in Code listing 7.1. The complete data model code can be found in Appendix A, and a preview is provided in Figure 7.8.

Code listing 7.1: Data type for gas detectors in GraphQL code.

```
type GasDetector {
  tag: String!
  description: String
  platform: Platform
  objectType: ObjectType
}
```

Code listing 7.1 defines "type GasDetector", which results in a block in the data model preview. The defined data types correspond to the entities outlined in the data model design from Figure 6.3. For example, the gas detector type in the data model resembles the gas detector entity from the design. This is illustrated

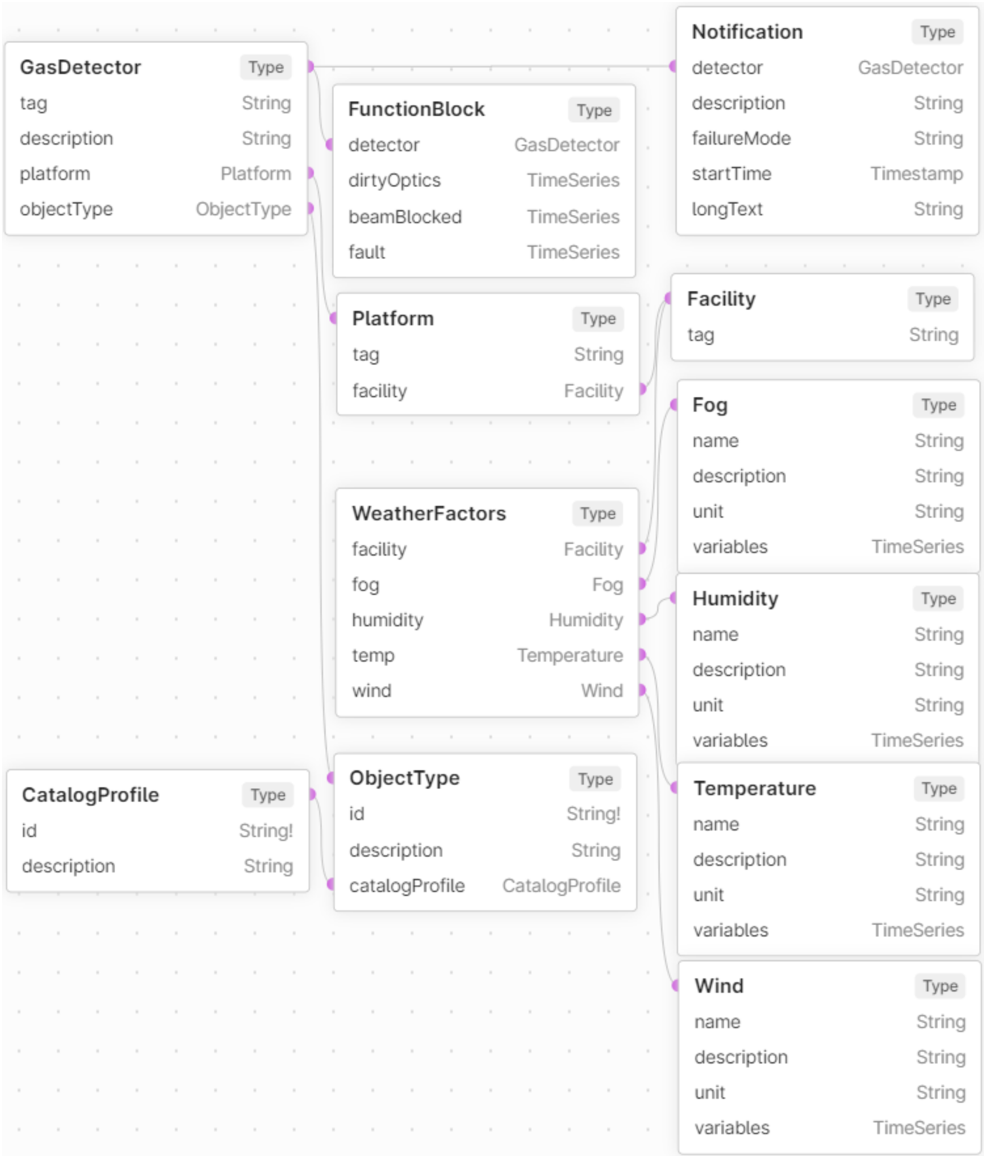

Figure 7.8: Data model in CDF.

in Table 7.5. Both the name of the entity and data type and their associated attributes represents the same. The difference is syntax, where space cannot be used in GraphQL variable names. In addition, the ID has been specified as the tag in the data model. Another difference is that the data type specifies the value types. The tag is a "String!" value. This means that the value is string, and the exclamation mark indicates that the field must be included for an instance of the gas detector type. Hence, gas detectors without tags cannot be considered by the data model.

The type of data is specified to the right of the attribute types in both the code and the data model preview. The defined data types can also be used as types of

Table 7.5: Gas detector data type and design entity.

	Entity	Data type
Name	Gas detector	GasDetector
Attributes	ID	tag
	description	description
	platfrom	platform
	object type	objectType
Source	Data model design	Data model implementation

data in the model. This is for example seen in the gas detector type where the platform is of the "Platform" type and the objectType is of the type "ObjectType". Figure 7.8 shows this by connecting platform and objectType to the defined data types "Platform" and "ObjectType".

The design encompasses eight entities, while twelve data types are defined by the data model. This is because separate data types were created for various weather factors. This allows for easy modification of which weather factors are considered and also enables the inclusion of attributes for each weather factor. Similar modifications could be applied to the function block time series, although there is typically more certainty regarding the relevant time series compared to weather factors. Furthermore, there is less need to describe attributes for the Boolean time series.

7.4 Integration

The extraction of data from data sources and the transformation to the CDF data model is not within the scope of this thesis. To integrate the necessary data into the solution data model, the data needs to be mapped from the CDF data model. Figure 7.9 outlines the results for the relevant detector data.

CDF transformations are used to populate the data model. A transformation is created for each data type that requires population, and separate transformations are made to define relationships between two data types. CDF Transform Data provides two editor options: the mapping editor and the structured query language (SQL) editor. The mapping editor is a no-code editor with some limitations for complex queries. It offers a visually intuitive structure where data elements are directly matched to data type properties. The mapping editor is typically used for copying data from source to target resource types, while SQL queries are employed for more intricate transformations (Cognite, 2022).

The intention for this thesis was to use the mapping editor, as the relevant data had been transformed and contextualised as part of the data preparation. Furthermore, the data model was designed to align with the available data, allowing for straightforward copying of the data into the model. However, this posed a challenge for three reasons. As a result of these challenges, populating the data model

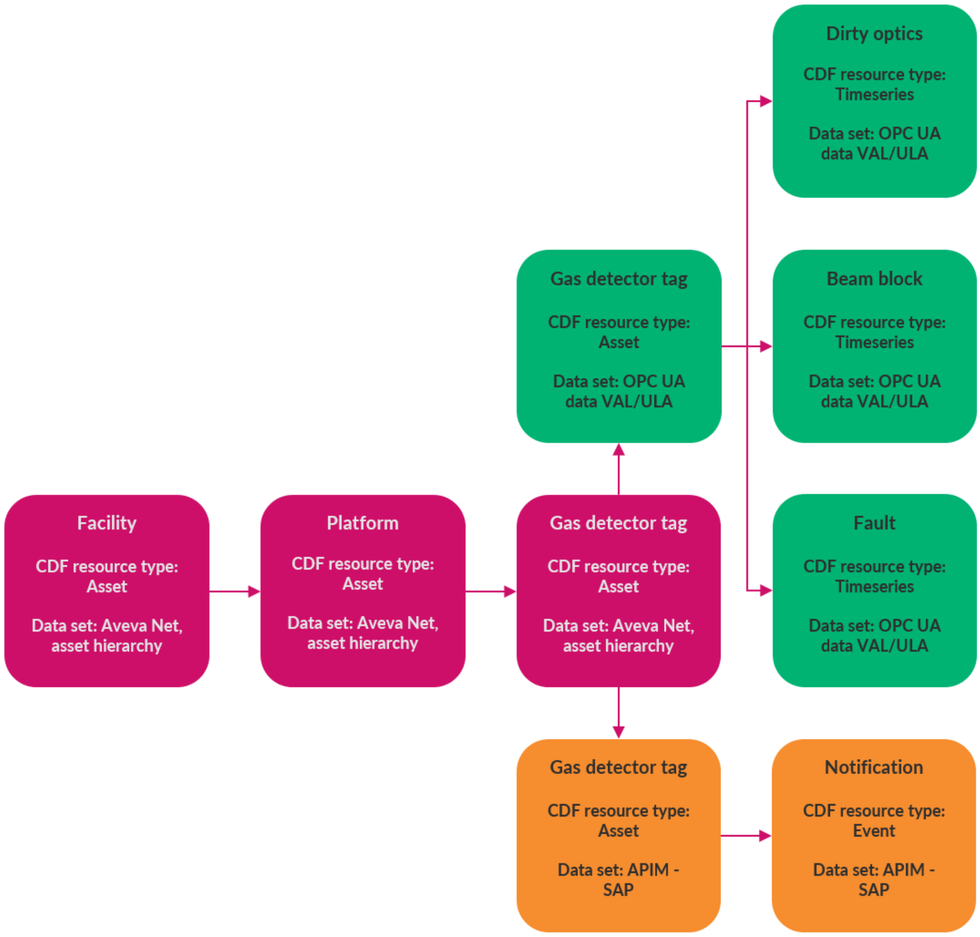

Figure 7.9: Gas detector data hierarchy.

was not accomplished as part of this thesis.

Firstly, the data sets could not be selected as a source for data transformation. When mapping data in a transformation, one must choose from three categories of sources: raw data in the CDF staging area, CDF resource types, or user-defined data models.

Secondly, filtering the data from the selected source was challenging. For example, if "assets" under CDF resource types were chosen as the source to populate the facility type, all objects of the asset type in the CDF project would be ingested. Even if specifying the data set was an option, the mapping editor would still include all assets in, for instance, the "Aveva Net, asset hierarchy," without the ability to specifically filter out line gas detector receiver objects.

The third challenge pertains to the mapping editor's handling of object meta data as an object. It is not possible to gather specific metadata attributes, and the list of easily accessible parameters is quite limited. Therefore, obtaining, for instance, the function block time series is not straightforward.

Chapter 8

Discussion

The discussion chapter is divided in two sections. The first section looks at the data model and to what degree it meets the specifications from Chapter 6. The section first looks at the entities and attributes in the data model against the system requirements. Next, the section looks at the use case and how it could be achieved. The section also discusses the impact the specified data model could have on safety related to gas detection SIS. In the second section, the use of CDF is discussed, including possible future use cases.

8.1 Data Model Results

8.1.1 Requirement Specification

Section 7.3 and Section 7.4 makes it clear that the data model is implemented with FDM but data is not integrated through CDF. The first system requirement is therefore acquired, but the second is not. Integrating data through CDF is a necessary step for utilising the data model.

1. The data model shall be implemented with FDM.
2. The data model shall integrate data through CDF.

The remaining system requirements detail the data model entities, attributes and relationships. Information about the entities and their attributes from the data model design in Chapter 6 are all found in CDF. The data that is available in CDF is presented in Chapter 7. Since the data model has not been populated, the further discussion examines if the system requirements are acquired by the data model. It is assumed that the requirements could also be acquired by a populated data model given system requirement two.

The use case and the information needed for constructing the data model are outlined in Chapter 6. The data model design is made with regard to the system requirements and the data model presented in Section 7.3 organises the information from the design. Hence, the first system requirements from the requirement specification are realised. These system requirements consider the entities from the design, which relate to the data types in the data model.

3. The data model shall structure gas detectors in the Aker BP equipment hierarchy.
4. The data model shall structure weather conditions.
5. The data model shall structure gas detector events, looking at dirty optics, beam block, and fault.
6. The data model shall structure gas detector notifications.
7. The data model shall include the object type and catalog profile for equipment.

The entire equipment hierarchy is not included, but the gas detectors are organised as belonging to a platform, which again is a part of a facility. The chosen structure for weather conditions is that a weather factor entity consists of various weather factors that all belong to a facility. The weather factors fog, humidity, temperature and wind have been included and are listed in the "WeatherFactors" type. Each of these weather factors are defined in separate data types, where name, description and unit is included in addition to the time series with measurements or weather predictions.

It is easy to add, remove or change which weather factors are included in the model. This could have been made even more simple if the "WeatherFactors" type included the measurements directly. The measurements could be listed directly in the "WeatherFactors" type, but this would make it difficult to include descriptions and units for the different weather factors. Instead, it could be solved like in Code listing 8.1. The alternative weather factor type includes only one weather factor, but the different types of weather factors can all be used as this weather factor. The name, description and unit fields would separate the different weather factors that are now disjoint in separate data types. Because the weather factors would not be explicitly defined in the data model, there is no limitation of the different weather factors and which factors are included can be changed independent of the data model. The advantage of the implemented data type for weather factors with the weather factors defined separately is that it could make it easier analysing how the different weather factors impact the gas detector events. However, this should also be possible with the weather factor type in Code listing 8.1. It requires an extra filter for looking at specific types of weather factors when using the query explorer, and for the weather types to be correctly defined in the "name" attribute, or in a separate field for the type of weather factor.

Code listing 8.1: Alternative data type for the weather factors.

```
type WeatherFactor {
  name: String!
  description: String
  unit: String
  facility: Facility
  variables: TimeSeries
}
```

The time series dirty optics, beam block and fault are included in a MA_FG function block type and seen in relation to the associated gas detector. However, the fault time series may not be necessary since it is almost equivalent to the beam block. The data sets containing OPC UA data from the control system contain alarms and events stored in the CDF resource type "event" in addition to the "time series". These have not been included in the data model because events beyond dirty optics, beam block and fault were deemed unnecessary for the use case. The events in the OPC UA data also contains information about the activation and deactivation of the relevant factors, however, it seemed simpler to analyse the time series than each distinct event.

Notifications are also seen in relation to the associated gas detector. The start time is included for connecting the notifications to events from the function block. Failure mode is included for filtering the notifications that may concern function block events. All notifications with failure mode "LOO" will be connected to the MA_FG function block, because it is the control system that provides the loo. Even with the failure mode one will not find all the relevant notifications. An area tag will typically be used for notifications concerning cleaning of detector lenses due to fog. Because of this, the notification is not directly linked to the specific gas detector tags. These notifications are difficult to find and utilise in the data model. The failure data from notifications are stored in a free text field. Using the failure data in a data model therefore requires natural language processing. This functionality is not available in the CDF data modelling tool, but could be applied in an application.

Object type and catalog profile is included for the gas detectors in the data model. The ID is the code giving the name of the object type and catalog profile. The description field explains which equipment groups that belong in the named category.

The data types weather factors, function block and notification could also have ID attributes. This does not contribute to the analysis of the gas detector fault and weather relationship, but makes it easier to distinguish the instances of the data types. This can be an advantage for ensuring data quality.

The next system requirements are also fulfilled by the data model. These requirements consider the entity attributes. The last system requirements consider the relationships of the data model. Two of these requirements are also attained.

8. The data model shall include gas detector tag for gas detector events, and notifications.
9. The data model shall include geographical data for the gas detectors.
10. The data model shall include geographical data for the weather data.
11. The data model shall include the timestamps for weather data, gas detector events, and notifications.
12. The data model shall connect the gas detectors with their associated object type, gas detector events, and notifications.
13. The data model shall connect gas detectors and weather data to their associated facilities.

The gas detectors are connected to their associated object type. The object type can be used for finding all notifications and work orders related to an equipment group. The gas detectors are connected to their associated events and notifications in that the function block and notifications contain the detector tag. The weather data and gas detector events are both time series, which means that the variables are related to timestamps. For notifications, the start time is included as a timestamp.

The gas detectors and weather data are connected to their associated facilities. The facilities also give the necessary geographical data and make it possible to find the weather conditions in the area of a gas detector. In addition to the geographical data it could be useful to include an attribute defining the type of area the gas detector is situated.

Some areas on a facility are more exposed to gas; gas leaks are also more dangerous in some areas than others. The hazardous area rating from the asset hierarchy gives an indication of how exposed an area for gas in dangerous quantities. There is also a great variation of how exposed the areas are to the weather conditions. An example is air intakes, which are typically located on the outside of a platform. Air intakes are therefore exposed to the weather and also a dangerous place for a gas leak. The area types have an impact on the requirements for gas detection SIS from NORSOK S-001, 2021. It could be relevant to include these parameters in the data model. For example, it is the most interesting to analyse the weather dependability of detectors that are weather exposed. However, there is no parameter in CDF for labelling how weather exposed an area is. The facility area code and service description from the asset hierarchy can give information about how weather exposed the area is but it requires knowledge about the platform to deduce this information. It is therefore difficult to utilise in a data model.

The final system requirements concerning relationships are not fulfilled by the data model. These connections between entities are based on timestamps, which are not explicitly defined in the data model.

14. The data model shall merge gas detector fault events with corresponding weather parameters based on timestamps and geographical associations.
15. The data model shall connect notifications to gas detector events based on timestamps.

The gas detectors are connected to the associated notifications, events and facilities. The weather factors are also connected to facilities. Connecting specific events, notifications and weather conditions together requires the timestamps that are stored in the time series.

8.1.2 Use Case Specification

The three main goals of the use case are avoiding failures in gas detection SIFs by using the data model for predictive maintenance, identifying bad actor gas detectors, and improving management of resources. These goals were not fulfilled in this master thesis. To accomplish the goals, the relationships between the detector fault events and weather conditions must be identified and analysed. The data model establishes the relationship so that it can be analysed when the data model is populated.

Populating the data model was prevented by the maturity of CDF and the Aker BP process of integrating their data to CDF. However, it should be possible now despite expected updates to CDF and event though the data is not yet accessible for all the facilities. The data model is made to be facility independent, so that it can be tasted for Ula and Valhall, and then expanded to the other facilities when they are ready. The Aker BP object types facilitates for systematic loading of IR line gas detectors and associated data within various systems. With sufficient time and resources this should be possible to utilise in FDM.

The data in a populated data model can be accessed with the FDM query explorer. This can be used for categorising the gas detectors. The gas detectors with frequent fault events can be filtered and based on the location different measures can be considered. This can be small activities, like shielding the detector better, or larger measures, like installing a different type of detector. It is important to base these decision on analysis, to ensure that the gas detection SIS works optimally.

Achieving better resource management and predictive maintenance requires a predictive model and real time monitoring. The gas detectors are already monitored, so this must be linked to the model. For making a predictive model, a machine learning algorithm is dependent on a large data basis of historical data. Aker BP has such historical data, but for a machine learning algorithm to be able to utilise this data for learning, it might need data that is already analysed. This means that the past incidents are categorised. If using machine learning for classifying which incidents were likely caused by the weather, without having a correct solution, one cannot know if the machine learning categorisation is correct. However, a model does not have to be a hundred percent accurate in order to be useful and profitable.

A possible approach is looking at how the weather was when the gas detectors previously got dirty optics or were beam blocked. The model can then be made to assume that the detectors will behave equivalently when similar weather conditions are predicted by the weather forecast. With this start point, a machine learning algorithm can gradually improve.

It is particularly important to consider safety if machine learning is to be used for analysis of the gas detection SIS and weather factors. Artificial intelligence is often based on complex models that are difficult to understand. The motivation for using it is that it works well for analysing complicated systems. Manual analysis alone is not feasible for the use case due to the volume and complexity of the data involved. It is thus difficult to understand and verify the decisions made by the machine learning algorithm.

The utilisation of a data model in predictive maintenance is expected to reduce the need for corrective maintenance. However, it would not have an impact on the function tests of the SIS, unless it ultimately enhances the reliability of the gas detector, which in turn affects the PFD. However, it is unlikely that the data model, which primarily focuses on detecting dirty optics and beam blockage, would significantly improve the PFD, as these issues are not the types of failures considered in PFD analysis.

The data model would serve as an additional tool alongside existing maintenance practices and SIS follow-up activities. As a result, the data model would contribute to enhanced safety without compromising maintenance quality. Even if the data model does not perform optimally, it would result in reduced predictive maintenance while corrective maintenance would continue as usual.

8.2 CDF Suitability and Opportunities

CDF serves as an optimal starting point for constructing data models that form the foundation for analysis. CDF is specifically designed to gather and integrate all the required data, providing a comprehensive and structured repository for conducting the analysis effectively. Having quantities of data accessible in CDF is a base for data-driven decision. Ensuring better decision-making is one of Aker BP's ambitions.

In addition to the quantity of data, the quality is equally important for the success of data models and data-driven decisions. CDF makes this easier to maintain with the data flow process ensuring quality tested data in the main CDF project. Contextualising of data in CDF makes it more useful.

Consistent use is one of the difficult aspects of data quality. Even though categories are defined to organise data, it is difficult to find categories that everyone understands in the same way. For example, fault codes might be defined differently between facilities and engineering companies might not understand the Aker BP object types. Inconsistent data leads to a weakened data basis when filtering data for analysis.

The gas detector data model could be further developed to check any number of aspect against the weather conditions. It could for example include the detector model, it's hardware or materials. The challenge with this is acquiring the details for all the detectors in a consistent way.

In addition to further developing the gas detector data model, CDF is suitable for developing new data models. The requirement of PFD verification in the SIS monitoring, verification and analysis life cycle phase, would be applicable as a data model in CDF. The model would collect the result of SIS function tests, for updating and monitoring of the equipment DU failure rates. CDF could also help organising information for simpler reporting to RNNP.

Chapter 9

Conclusions and Further Work

9.1 Conclusions

In conclusion, this master thesis has presented a comprehensive data model for monitoring optical gas detectors, specifically focusing on the use case of SIS follow-up. The operational phase of an SIS requires continuous monitoring and maintenance to ensure optimal performance and system reliability.

Chapter 2 provided an overview of different types of gas detectors, categorising them as point detectors or line detectors based on their design principles. It emphasised the advantages of optical gas detectors, particularly IR detectors, for detecting hydrocarbon gases. IR detectors offer faster response times, improved reliability, and self-diagnostic capabilities compared to some other types of detectors. However, they can be susceptible to failures due to factors like condensation on the lens and adverse weather conditions. The chapter highlighted the importance of combining different types of detectors to enhance gas detection probability.

Chapter 3 introduced the RAMI 4.0 model, which describes the key features of Industry 4.0. The RAMI 4.0 layers, including the business layer, functional layer, information layer, communication layer, integration layer, and asset layer, were applied to describe the gas detection SIF. Furthermore, maintenance strategies were discussed, with a focus on predictive maintenance using condition monitoring and historical data analysis to anticipate failures.

Chapter 4 presented how Aker BP utilises tags to uniquely identify and track individual equipment within their facilities. Catalog profiles and object types were implemented to establish consistency in equipment categorisation across their facilities, considering factors such as failure data and equipment function. Aker BP utilises data analysis and predictive maintenance techniques, including real-time monitoring and predictive analytics, based on weather forecast data to identify faults and predict future conditions for F&G detectors at their facility Edvard Grieg.

Chapter 5 discussed the data tools and systems employed, including the CDF platform that integrates data from IT and OT systems, enabling better decision-making and solution development. Aveva Net and SAP are used for storing and managing asset information and maintenance data, while SAS provides integrated safety and automation control. The OPC UA communication protocol is utilised for SAS.

Chapter 6 presented the problem and solution spaces of the use case specification. The problem space involved weather conditions causing dirty optics and beam block in optical gas detectors, which required time-consuming reactive maintenance measures. The solution space focused on optimising maintenance planning, utilising available resources efficiently, and avoiding failures caused by adverse weather conditions. The data model proposed in the requirement specification aimed to visualise patterns between failures in gas detectors and weather conditions, enabling the anticipation of expected failures and facilitating maintenance scheduling. The system requirements specified the integration of data from various sources, including historical weather data, diagnostic alarms, fault events, and notifications, incorporating timestamps and geographical data. The chapter also developed a system architecture and design for the proposed data model. The data model design included the entities gas detectors, platforms, facilities, weather factors, object types, catalog profiles, function blocks, and notifications, with associated attributes.

Chapter 7 discussed the storage of gas detector data, maintenance information, and weather data in CDF. The data model was implemented using FDM, defining data types based on the design specification. The integration of data into the data model involved mapping the data from different CDF data sets to the corresponding data types in the model. Populating data models is done using the CDF transformations. However, there were challenges with the transformations mapping editor. The CDF data sets could not be selected as a source for transformation and the data from the selected source were difficult to filter. This lead to the data model not being populated.

Chapter 8 served as a discussion section, emphasising the necessity of integrating data through CDF to effectively utilise the data model. Although the use case goals of avoiding failures in gas detection SIFs, identifying bad actor gas detectors, and improving resource management were not fully achieved in this thesis, suggestions were made for further works to populate the data model and leverage machine learning algorithms for predictive maintenance and analysis of the relationship between gas detectors and weather conditions. The quality of data in CDF was highlighted as a critical factor for successful data models and data-driven decision-making.

Overall, the data model presented in this thesis serves as am additional tool to complement existing maintenance practices and SIS follow-up activities, contributing to enhanced safety and maintenance quality. Further attention is recommended for refining entity relationships and addressing timestamp-related aspects, when the data model is populated, to fully realise the potential benefits of the data model in improving gas detector reliability.

9.2 Further Work

Further Development of the Data Model

The continuation of this thesis work involves integrating data from relevant sources within the CDF data sets into the existing data model. Statistical analytics techniques can then be applied to the collected data, enabling insights into the relationship between weather conditions and gas detection faults. By linking the data model to real-time monitoring of gas detectors and weather predictions, predictive analytics can be implemented. This enables data-driven decision-making and predictive maintenance based on the analysis results. The insights gained from statistical analytics and predictive models inform operational strategies, improve safety measures, and optimise resource allocation. Furthermore, implementing predictive maintenance practices based on the data analysis helps prevent equipment failures and reduce downtime. Overall, this thesis work contributes to the development of a comprehensive data-driven framework for gas detection fault analysis, predictive maintenance, and informed decision-making within Aker BP.

Expansion of the Data Model

The gas detector data model can be expanded to incorporate further factor for analysis. By including information such as the detector model, hardware specifications, and materials, along with relevant weather data, Aker BP can gain insights into the performance and reliability of various gas detectors under different weather conditions. However, careful attention should be given to acquiring consistent and reliable data to ensure accurate analysis.

Development of New Data Models in CDF

In addition to the gas detector data model, Aker BP should explore the development of new data models within CDF. For example, a data model focused on the verification of PFD in the SIS monitoring and analysis life cycle phase could be created. This model would collect and track the results of SIS function tests, allowing for equipment failure rate monitoring and updating. This would contribute to improved safety and compliance in Aker BP's operations.

CDF data models can also be leveraged to organise information and streamline reporting to regulatory bodies, such as the RNNP. By structuring and integrating relevant data in CDF, Aker BP can simplify the reporting process, ensuring timely and accurate submissions while complying with regulatory requirements.

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Special Aker BP Terms

asset Functional equipment or logical groups of equipment. In CDF it means a digital representation of physical objects or groups of objects.
Source: Aker BP, 2023a.
Entity which is owned by or under the custodial duties of an organisation, having either a perceived or actual value to the organisation.
Source: Plattform Industrie 4.0, 2023a.

catalog profile The equipment in each functional location is connected to a catalog profile, which defines traits of that equipment in regards to which failure data is relevant for that type of equipment.
Source: Aker BP, 2023a.

functional location A unique code that defines the functional location and function of a physical component within a facility. The "functional location" only refers to where the tag is located within the system, not the precise physical position.
Source: Aker BP, 2023a.

object type The object type is a sub-category of catalog profile, which may also consider the function.
Source: Aker BP, 2023a.

tag See functional location.
Source: Aker BP, 2023a.

Appendix A

Data Model

Code listing A.1: Data model in GraphQL Data Modeling Language.

```
type Facility {
  tag: String
}
type Platform {
  tag: String
  facility: Facility
}
type GasDetector {
  tag: String
  description: String
  platform: Platform
  objectType: ObjectType
}

type CatalogProfile {
  id: String!
  description: String
}
type ObjectType {
  id: String!
  description: String
  catalogProfile: CatalogProfile
}

type FunctionBlock {
  detector: GasDetector
  dirtyOptics: TimeSeries
  beamBlocked: TimeSeries
  fault: TimeSeries
}

type Notification {
  detector: GasDetector
  description: String
  failureMode: String
  startTime: Timestamp
  longText: String
}

type WeatherFactors {
```

```
  facility: Facility
  fog: Fog
  humidity: Humidity
  temp: Temperature
  wind: Wind
}
type Fog {
  name: String
  description: String
  unit: String
  variables: TimeSeries
}
type Humidity {
  name: String
  description: String
  unit: String
  variables: TimeSeries
}
type Temperature {
  name: String
  description: String
  unit: String
  variables: TimeSeries
}
type Wind {
  name: String
  description: String
  unit: String
  variables: TimeSeries
}
```

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