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Towards Predictive Maintenance in District Heating

A Case Study of Inspection Practices in District Heating Chambers

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Civilingenjörsprogrammet i system i teknik och samhälle

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Abstract

District heating (DH) networks form a central part of the energy infrastructure and ageing components increasing the need for effective and forward-looking maintenance strategies. The aim of this study is to investigate current inspection and maintenance practices within DH chambers, and to analyse how predictive maintenance can be developed to improve maintenance planning and extend the asset lifetime.

The study was conducted as a qualitative case study of Vattenfall´s DH network in Uppsala, combining a literature review with empirical data collected through semi-structured interviews and document analysis. The analysis focuses on inspection routines, data collection and usage, decision-making processes, and which predictive maintenance methods are feasible given current organisational and technical conditions.

The results show that inspections are currently based on fixed intervals and that digital systems are primarily used for documentation rather than analysis. Although relevant data is collected, the potential for predictive maintenance is limited by insufficient system integration, variations in data quality and fragmented historical data. Furthermore, maintenance decisions are largely experience-based and reactive.

A modified Failure Mode and Effects Analysis based method is identified as a suitable first step towards implementing predictive maintenance, as it builds on existing working methods whilst enabling more structured and traceable prioritisation. In the longer term, more advanced methods, such as Discrete Hidden Markov Model, may become relevant. The study indicates a need for a step-by-step development, where both technical solutions and working methods evolve in line with the organisation’s maturity.

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Populärvetenskaplig sammanfattning

Fjärrvärme är en viktig del av energisystemet i många svenska städer. I stället för att varje byggnad har ett individuellt uppvärmningssystem produceras värme centralt och distribueras till kunderna via ett fjärrvärmenät. Det gör fjärrvärme till ett effektivt sätt att värma upp byggnader. Samtidigt är många fjärrvärmenät generellt gamla. De har byggts ut under lång tid och består av komponenter från olika tidsperioder, vilket gör underhåll till en viktig fråga.

Denna studie behandlar fjärrvärmenätet i Uppsala, som ägs och drivs av Vattenfall. Nätet har varit i drift sedan 1960-talet och består av både äldre och nyare sektioner. Studien avgränsas till fysiska inspektioner av fjärrvärmekammare, ett utrymme under marken där viktiga delar, såsom ventiler, rörkopplingar och andra komponenter kan nås. Kammare är därför viktiga för att kunna kontrollera, underhålla och reparera nätet.

Syftet med uppsatsen är att kartlägga hur inspektioner av fjärrvärmekammare genomförs idag, vilka eventuella hinder som finns för ett mer prediktivt underhåll och hur arbetsprocesserna kan förbättras för att främja detta. Prediktivt underhåll innebär att förutse fel innan de uppstår. Detta kan underlätta underhållsplanering, minska behovet av akuta åtgärder och bidra till en mer resurseffektiv drift. Ytterligare undersöker studien vilken prediktiv metod som är mest lämplig att implementera med hänsyn till organisationens nuvarande förutsättningar. Studien baseras huvudsakligen på intervjuer med personer som arbetar med underhåll, planering och digitala system inom fjärrvärme. Detta kompletteras med en dokumentstudie av interna dokument och digitala system som används i dagens inspektionsarbete.

Resultaten visar att dagens inspektioner till stor del är tidsstyrda. Kammare inspekteras med fasta intervall, beroende på hur viktiga de anses vara för nätet. Detta ger en tydlig struktur, men innebär också att inspektionerna inte styrs av kammarens skick eller tidigare fel. Studien visar också att det finns stor kunskap bland tekniker och projektledare. De som arbetar med nätet har praktisk erfarenhet och gör många kontextuella bedömningar. Detta kan vara en styrka eftersom varje situation kan skilja sig åt, men det kan också leda till att bedömningar blir svåra att jämföra. Detta skapar utmaningar med att använda inspektionsdata för att analysera hur fel utvecklas över tid. Ännu en slutsats är att det finns tillgång till olika data, men att den inte används på ett sätt som stödjer prediktivt underhåll. Information finns i olika digitala system för inspektioner och felhantering, men systemen kopplas inte samman på ett effektivt sätt. Data används främst för dokumentation och uppföljning, snarare än för att analysera mönster eller för att förutse framtida fel.

För att kunna arbeta mer prediktivt krävs därav inte bara mer data utan bättre och mer användbara data. Informationen behöver vara mer konsekvent, mer jämförbar och tydligare kopplad till specifika kammare och komponenter. Återkommande åtgärder kan vara tecken på underliggande problem och om sådana händelser inte dokumenteras på ett enhetligt sätt kan det bli svårt att identifiera mönster. Vidare visar studien att avancerade prediktiva metoder, såsom maskinlärning eller statistiska modeller, i dagsläget är svåra att implementera. De kräver stora mängder strukturerade och tillförlitliga data. I stället föreslår studien en mer strukturerad metod för att prioritera fel. En sådan metod är Failure Mode and Effects Analysis (FMEA), som används för att bedöma fel utifrån hur ofta de kan uppstå, hur allvarliga konsekvenserna blir och hur lätta de är att övervaka eller hantera.

Sammanfattningsvis visar studien att det finns möjligheter att utveckla underhållet av kammare i Uppsalas fjärrvärmenät, men att det bör ske stegvis. Det första steget är inte att införa avancerade modeller, utan att förbättra kvaliteten på den data som samlas in, koppla samman information från olika digitala system och skapa tydligare kriterier för hur fel ska prioriteras. På så sätt kan underhållsarbetet bli mer konsekvent, mer transparent och bättre anpassat till ett åldrande fjärrvärmenät.

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- *Elsa and Jonna*

Abbreviations

ACE	Asbestos Cement	Pipe material composed of cement reinforced with asbestos, used in older infrastructure.
DCS	Distributed Control System	Control system where control functions are distributed across multiple units.
DH	District heating	System for distributing heat through a network of pipes to buildings.
DHMM	Degradation Hidden Markov Model	Probabilistic model used to describe and predict the gradual degradation of components over time.
DN	Diameter Nominal	Standardised size designation used for pipes, valves, and fittings.
ERP	Enterprise Resource Planning	System used to manage and integrate core business processes such as finance and resource planning.
FMEA	Failure Mode and Effects Analysis	Systematic method for identifying and prioritising potential failure modes based on risk.
GIS	Geographic Information System	System used to capture, store, analyse and visualise spatial and geographic data.
MES	Manufacturing Execution System	System used to monitor and manage production processes in real time.
MPN	Maintenance Priority Number	Modified version of RPN adapted for maintenance prioritisation.
PE	Polyethylene	Plastic material used as an external casing for pipes.
PLC	Programmable Logic Controller	Digital controller used to automate industrial processes.
POTH	Peaks Over Threshold with Historical Information	Statistical method for analysing extreme values using both recent and historical data.
PUR	Polyurethane	Insulation material used around pipes to reduce heat losses.
RPN	Risk Priority Number	Numerical value used in FMEA to rank failures based on likelihood, severity, and detectability.

SCADA	Supervisory Control and Data Acquisition	System used for real-time monitoring and control of industrial processes.
Trimble NIS	Trimble Network Information System	System used to store and manage information about infrastructure networks.
UTG	Utility To Go	Field-based digital tool used for inspection and data collection.

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1. Introduction

District Heating (DH) systems constitute a key component of the energy infrastructure in many European countries. It plays an important role in Sweden, where DH networks supply more than half of the building's total heat demand (Fälting et al., 2025). These systems are characterised by large upfront capital investments and components with long technical lifetimes, often exceeding 40-50 years. This makes DH a feasible solution from a life-cycle perspective (Danish Energy Agency, 2017).

However, the long service life of DH infrastructure also implies that many existing networks consist of ageing assets. This ageing is increasing the need for efficient, systematic maintenance and asset management strategies (Rafati and Shaker, 2024).

Ageing pipelines and components are subject to material degradation. Mechanisms such as corrosion, insulation deterioration and mechanical fatigue can result in heat losses, leakages and unplanned outages (Bahlawan et al., 2022; Gadd and Werner, 2015). Previous studies have shown that failures in DH networks are correlated with pipe age, installation methods and local ground conditions (Sällström et al., 2026). Consequently, operators of large-scale DH systems face growing challenges in prioritising maintenance activities and ensuring long-term operational reliability while controlling costs (van Dreven et al., 2023).

Historically, maintenance of DH networks has relied on time-based or reactive strategies, where inspections are carried out at predefined intervals or when failures have already occurred. Such approaches risk being inefficient, either by allocating resources to unnecessary inspections or by failing to detect emerging faults at an early stage (Rafati and Shaker, 2024). In response to these limitations, predictive maintenance approaches where asset condition data and historical information are used to anticipate future failures have gained increasing attention within the energy sector (Löfblad et al., 2019). Research indicates that predictive maintenance can reduce operational expenditures, minimise unplanned downtime, and extend the useful life of infrastructure assets (Ahmed Murtaza et al., 2024).

The DH network in Uppsala has been in operation since the early 1960s. As a result, parts of the grid are approaching the end of their technical lifetime and are undergoing continues renovation (Vattenfall AB, 2025). In line with Vattenfall's long-term ambition to achieve net-zero emissions by 2040, optimising the performance and lifespan of existing infrastructure has been identified as a strategic priority (Vattenfall AB, 2026a).

Improved inspection practices and data-driven maintenance planning may therefore contribute to increased operational reliability and reduced environmental impact by postponing resource-intensive reinvestments.

Against this background, this master's thesis is conducted as part of a broader initiative within Vattenfall aimed at strengthening the organisation's capability to manage ageing assets within the Uppsala network (Vattenfall AB, 2025).

This study focuses on the DH network in Uppsala and examines how physical inspections in DH chambers are currently performed, which challenges and limitations can be identified, and how structured use of data and predictive methodologies could improve maintenance planning. By combining a literature review with empirical insights from current practices, the thesis seeks to develop recommendations that can support more efficient inspection processes, extend asset lifetimes, and lead to a more resilient DH system.

1.1 Aim and Research Questions

The aim of this project is to investigate current inspection and maintenance practices within district heating chambers and to analyse how these practices can be developed towards a more predictive maintenance approach.

This will be done by answering the following research questions:

- How are physical inspections conducted in the district heating chambers, and what constraints may hinder the development of predictive maintenance processes?
- Which predictive maintenance method is most suitable given the current inspection conditions?
- How can the organisation establish the conditions required to support the selected method and enable a transition towards predictive maintenance?

1.2 Delimitations

This study focuses on the physical inspections of chambers within Vattenfall's DH network in Uppsala. While some related pipeline segments will be considered, the broader pipe network and production or customer-side facilities fall outside the scope of this work. The study primarily addresses inspection activities, including both planned inspections and unplanned inspection-related activities such as acute incidents and leakages.

The analysis is limited to evaluating current inspection practices and identifying opportunities for improvement, mainly through data-driven or predictive approaches. The project involves developing a conceptual framework and should be viewed as a strategic and methodological recommendation rather than an operationally functional solution.

2. Background

The following chapter presents the contextual background relevant to the study. The chapter introduces the Uppsala DH network, the concept of predictive maintenance, and finally, previous research related to predictive maintenance in DH networks is reviewed.

2.1 District Heating Network in Uppsala

The DH network in Uppsala is currently one of the Sweden's largest and most comprehensive heating supply systems. It is Vattenfall´s largest network and consists of over 500 kilometres of pipelines, which have been gradually expanded over the past 60 years (Vattenfall AB, 2025). The DH network covers large parts of Uppsala and supplies around 76,000 households, which corresponds to approximately 95% of all properties in the municipality. The system has an installed heat production capacity of 825 MW, including steam production (Vattenfall AB, n.d.a). In 2024, a total of 1,273 GWh of DH was supplied to business and private customers (Vattenfall AB Värme, n.d.).

The DH network in Uppsala consists of components with several different materials built over time, reflecting the age of the network and its gradual expansion during the years. Among the oldest main sections, the pipes are made of asbestos cement (ACE) and concrete with a steel media pipe. Approximately 66 kilometres of ACE pipes are still in operation. Repairs and handling of this material pose both operational safety challenges and occupational health and safety risks due to asbestos handling requirements. Most of these pipes are around 50 years old and include old chambers and culverts (Vattenfall AB, 2025). The network also consists of newer steel pipes insulated with polyurethane (PUR) and encased in polyethylene (PE), which are used for current renewal work (Vattenfall AB, 2025). There are also copper pipes and plastic pipes that are used as service pipes that connect the main pipes to the customer's substations (Vattenfall AB, 2025).

Chambers are important components of the DH network. They are underground structures, generally constructed from concrete, and can be accessible via manholes. Chambers are used as a point for operation, maintenance and inspection of DH networks. They contain various components such as fixings, compensators, flanges, valve assemblies and sensors inside, but the specific components present in each chamber vary (Svensk Fjärrvärme, 2015). A covered DH chamber is shown in Figure 1.

Figure 1. Covered DH chamber seen from above ground (Vattenfall, n.d.b).

2.2 Predictive Maintenance

Historically, predictive maintenance processes have often been seen as difficult to implement or too resource-intensive. The development of simpler and more accessible methods means that predictive maintenance can now be implemented with less extensive effort. Predictive maintenance has thus gone from being a challenge to becoming an opportunity, and in many cases a source of profit for companies (Barlow, 2015).

A key aspect of predictive maintenance is calculating the remaining service life of the equipment. The level of analysis can range from diagnostic, understanding why a fault occurs, to prescriptive analysis, which provides recommendations for optimising decision-making. For example, informing and optimising preventive maintenance so that a machine lasts until the next scheduled shutdown (Molęda et al., 2023).

Predictive maintenance involves increased digitalisation and transformation to gain a more concrete understanding of how the system and its processes function. Methods for predictive maintenance aim to facilitate decision-making and to reduce the reliance on human intuition in decisions, instead basing them on historical data. By utilising knowledge from data sources within the system and analysing the data, it becomes possible to implement new types of maintenance strategies, improve work and planning, and increase the efficiency and safety of the system (Molęda et al., 2023).

There are several driving factors for using predictive maintenance in industry and energy production. Primarily to reduce system downtime, cut costs, improve safety, health, the environment, and quality, and to extend the system's lifespan. Reports indicate that inappropriate maintenance strategies within industries can reduce production capacity by 5-20% and that digital maintenance can increase asset availability by 5-15% and reduce maintenance costs by 18-25% (Molęda et al., 2023).

2.3 Predictive Maintenance in District Heating

DH operators have long recognised the potential of predictive maintenance. Ageing pipelines and the costly and time-consuming replacements they require have sparked interest in optimising and prioritising maintenance efforts to extend component life, leading to the emergence of various types of predictive maintenance. All DH networks are different, so it is not as simple as implementing the same predictive maintenance methods in all of them. Rather, it depends on factors such as the characteristics of the network's, local environmental conditions, access to data and component types. Therefore, its use today is limited and still under development (Rafati and Shaker, 2024).

Research on maintenance practices within DH systems has expanded in recent years, driven by rising expectations regarding reliability, efficiency and data utilisation in ageing energy infrastructures. Much of the literature emphasises a transition from traditional, time-based and reactive maintenance approaches toward more structured and data-informed practices (van Dreven et al., 2023). Studies reviewing current maintenance strategies describe how utilities historically relied in scheduled inspections and corrective repairs, without systematic use of available operational data or advanced diagnostic frameworks, which limited the effectiveness of maintenance planning (Rafati and Shaker, 2024; van Dreven et al., 2023). As a response, there has been increased scholarly interest in more intelligent approaches to anomaly detection, pattern recognition and operational monitoring that can support earlier identification of developing faults (van Dreven et al., 2023).

To the authors' knowledge, much of the existing research on predictive maintenance in DH systems focuses on pipelines, substations, leakage detection and operational monitoring. Chambers have received less attention, even though they are important inspection points and contain components that are central to maintenance work. This makes chamber inspections a relevant area for further research.

A part of contemporary research has focused on intelligent fault detection and diagnosis, building upon machine-learning techniques applied to operational time series data. Studies demonstrate that clustering-based anomaly detection, regression models and ensemble learning techniques can identify deviations in supply-return behaviour, abnormal heat loads and malfunctioning substations well before these are noticed by customer or field personnel (Theusch et al., 2021; Lee et al., 2025). These developments highlight the potential of data driven methods to enhance inspection targeting, particularly in systems where sensor coverage is uneven and where manual inspections alone are insufficient to detect early-stage abnormalities.

Predictive maintenance in DH networks can be supported by technologies such as data analysis and prediction models to forecast faults and estimate remaining service life. These approaches work by collecting data from integrated sensor systems, data management platforms and analysis tools that enable real-time monitoring. Data collection can be based on several different measurement methods, including temperature and humidity sensors and flow meters (Rafati and Shaker, 2024).

There are three main reasons for why predictive maintenance should be introduced in DH networks: economic reasons, safety-related causes, and environmental considerations. Economically, the motivation is focused on expensive renovations due to the ageing pipe system. Predictive maintenance is considered an effective tool for avoiding unnecessary or misguided investments. From a safety perspective, DH involves environments with high temperatures, high pressure and high humidity, which makes the system particularly susceptible to corrosion and leaks. DH networks are often located in densely populated areas where the consequences of major incidents can be significant. Predictive maintenance can therefore be used to detect and prevent faults before they develop into serious safety issues. The environmental motives can be linked to the safety aspects. Leaks and pipe breaks can lead to environmental damage and contamination of soil and groundwater. In the transition to newer and more modern DH networks, the requirements for careful monitoring and stability in operation will become higher, given that operating temperatures will be lower and a larger proportion of renewable heat sources will be used. Predictive maintenance is highlighted here as a method for ensuring sustainability, reducing energy losses and enabling the DH of the future to be operated with as little environmental impact as possible (Rafati and Shaker, 2024).

3. Theoretical Framework

This chapter presents the theoretical framework that forms the basis for the analysis. It presents different maintenance strategies, followed by an overview of data requirements for predictive maintenance, predictive methodologies, and approaches for fault prediction. It concludes by introducing FMEA, a risk-based fault prioritisation framework. Although FMEA is not a predictive method, it is relevant to the study since it can support a predictive maintenance approach by structuring how potential faults are assessed and prioritised before they lead to more serious consequences.

3.1 Maintenance Strategies

The primary objective of maintenance management is the total optimisation of the asset life cycle. This involves maximising the availability and reliability of the asset's components to ensure that production systems consistently deliver the required output, at the specified quality level, and within designated time constraints (Pintelon and Parodi-Herz, 2008). As industrial installations have become increasingly automated and technologically advanced, maintenance management has evolved in complexity. Contemporary maintenance functions must therefore address both heightened technical demands and intensified business pressures, requiring managers to oversee complex and heterogeneous systems within dynamic operational environments (Pintelon and Parodi-Herz, 2008).

Maintenance strategies are generally classified into three principal approaches: reactive, preventive, and predictive maintenance. These strategies differ in temporal orientation and underlying assumptions regarding failure prevention and resource allocation (Pozzi et al., 2021).

Reactive maintenance, also referred to as “run-to-failure", involves operating equipment until a fault occurs, after which corrective action is taken (Swanson, 2001; Zhang et al., 2019). Typically, only minimal or temporary interventions are implemented to restore functionality, with permanent solutions deferred until necessary. While this approach requires relatively low upfront investment in labour and financial resources, it is associated with drawbacks. These include unpredictable production capacity, higher likelihood of severe equipment failures, increased long-term maintenance costs, and elevated levels of defective or out-of-tolerance output (Swanson, 2001). As a result, reactive maintenance is generally regarded as the least cost-effective strategy due to the cumulative impact of downtime and extensive repair requirements (Zhang et al., 2019).

Preventive maintenance, in contrast, involves scheduled interventions at predetermined time intervals or after a specified level of equipment usage (Swanson, 2001). Activities include component replacement, cleaning, adjustments, and systematic inspections to identify signs of deterioration. This approach reduces the probability of unexpected failures and extends the operational lifespan of assets. However, it requires planned interruptions, which may result in inefficiencies if maintenance is performed unnecessarily or too frequently (Swanson, 2001).

Predictive maintenance is a more advanced, data-informed approach in which potential failures are anticipated through monitoring and analysis. This enables maintenance actions to be performed at the most appropriate time, ideally just before a fault is expected to occur (Molęda et al., 2023). Often referred to as condition-based maintenance, this strategy aims to optimise both the type and timing of interventions based on the actual condition of the equipment (Swanson, 2001; Traini et al., 2021). By leveraging predictive insights, organisations can reduce unnecessary maintenance activities, minimise unplanned downtime, and extend asset life (Traini et al., 2021).

3.2 Data Requirements for Predictive Maintenance

In order to develop an advanced method for predictive maintenance, the data used must be of a certain volume and quality. To ensure the data collection is as effective as possible, it is important that the data does not all come from the same source. There should be several different systems generating data that can then be combined when the model is created. A system pyramid can illustrate the different types of data that should be included in a model to ensure it is of the highest possible quality (Molęda et al., 2023). This is illustrated in Figure 2.

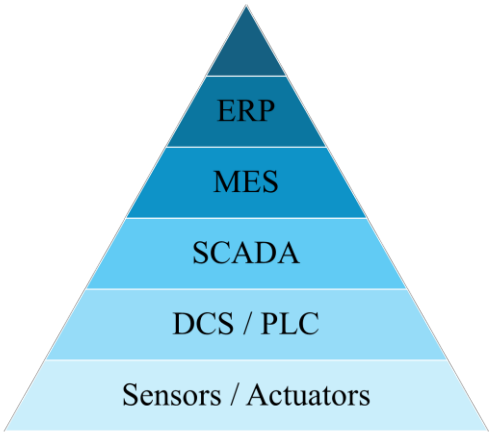

Figure 2. System Pyramid illustrating levels of data in a model

At the bottom of the pyramid are data from sensors located within the system that are to be analysed. Larger volumes of data are required, and it is therefore advantageous to source them from multiple sensors and components (Molęda et al., 2023). This layer is responsible for the physical execution of processes and generates raw data through condition monitoring techniques such as vibration analysis, thermography and motor current signature analysis. The resulting datasets often exhibit Big Data characteristics defined by the five Vs: volume, velocity, variety, value and veracity. Furthermore, this level includes actuators that physically manipulate control signals in real-time networks to drive installations (Molęda et al., 2023).

The next step in the pyramid is called command and control. It focuses on data from the production process itself and the nature of the human-machine interface to enable automated decision-making. This forms part of operational technology, encompassing Supervisory Control and Data Acquisition (SCADA), Distributed Control System (DCS), and Programmable Logic Controller (PLC) systems used to monitor and control physical processes and units in real time within industry. DCS and PLC systems automatically send control signals to equipment based on data from lower-level components, while SCADA functions as the main interface through which operators monitor and interact with the system. For larger systems, operational technology generates vast amounts of machine-generated logs and data. These are increasingly processed using edge computing to ensure low latency and high scalability close to the data source. These logs are then used in maintenance analysis and can be integrated with high-level business systems to provide insights into machine health, thereby also optimising maintenance planning (Molęda et al., 2023).

At the top of the pyramid, operational technology is complemented by data from Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES). These are integrated at an enterprise-wide level to enable advanced data analysis, representing a process known as vertical integration. This is achieved by combining data from both business and production systems (ERP and MES) with raw data from sensors and control systems (Molęda et al., 2023). Linking machine-generated data with human-generated records in the ERP system can transform existing data assets into actual business value. It also provides deeper insights into maintenance needs, including predicting faults and recommending optimal courses of action. Advanced applications at this level include the creation of digital twins, virtual models that simulate physical assets, and the implementation of prescriptive maintenance, which uses AI to recommend specific cost-effective actions (Molęda et al., 2023).

3.3 Predictive Methods

Predictive methods facilitate proactive maintenance planning by analysing system conditions and behaviour to anticipate future performance and potential failures. These methods differ in terms of complexity, dependence on data, and interpretability. Some methods rely on historical data and statistical relationships, whereas others are based on physical models, engineering knowledge, or rules about how a system should behave (Cerquitelli et al., 2021). Input data for predictive methods may originate from multiple sources, including physical sensors, real-time monitoring systems, historical operational records, and maintenance documentation (Cerquitelli et al., 2021; Ahmed Murtaza et al., 2024).

In practice, the choice of predictive methods is determined by factors including data availability and quality, system complexity, computational resources, and the capacity to accurately interpret the analysed process (Ippolito et al., 2021; Rafati and Shaker, 2024).

Overall, predictive methods provide the basis for shifting maintenance strategies from reactive responses to informed and anticipatory decision-making. However, their successful implementation depends on organisational factors such as data governance, digital system integration, and the alignment of analytical outputs and with existing maintenance workflows (Molęda et al., 2023).

Predictive methods are typically classified into three main categories: data-driven, model-driven, and knowledge-driven approaches (Zhang et al., 2019). In practice, these categories are often combined, resulting in hybrid approaches that integrate the advantages of multiple methods (Cerquitelli et al., 2021).

3.3.1 Data-Driven Methods

Data-driven methods are predictive approaches that use historical and observed data to identify a system's current damage and estimate its future degradation, particularly when physical understanding of the process is limited. Their defining feature is that the predictive model is derived directly from available data rather than from physical laws. Their advantages are that they can often be implemented with limited domain knowledge and can benefit from advances in computation and machine learning, thereby reducing model errors. At the same time, they are often difficult to interpret, since the relationship between input data and model output is not always transparent. Their performance also depends on the availability of sufficient and representative training data, and the resulting models may be difficult to transfer between different systems or operating contexts (Guo et al., 2020). There are several ways to work predictively within the category of data-driven methods, including data mining and machine learning (Greasley, 2019).

Data mining is the process of identifying patterns in complex and poorly defined datasets. This method is a central component of big data-driven analysis, which aims to extract insights from large-scale datasets to support organisational decision-making (Hang et al., 2023). Several specific techniques are used in data mining, including association rule mining, which involves identifying relationships between different objects that occur simultaneously (Greasley, 2019).

Another key technique in data mining is sequence identification, which aims to reveal the chronological order of actions or events. By mapping these chains, one can gain a deeper understanding of how individual actions lead to specific consequences or influence future events. Data mining also encompasses classification, where historical data is analysed to identify patterns that can be used to predict future behaviour (Greasley, 2019).

Machine learning is an iterative process that uses prepared training and test data to develop an analytical model. The aim is to generate uncertainty scenarios with the same probability distribution as the historical data. The objective is to capture randomness and volatility to assess operational reliability (Hang et al., 2023). This analysis tool offers several techniques, depending on the purpose. For example, learning can be either supervised or unsupervised. In supervised learning, both the input data and the known output data are available. The objective of this approach is typically classification or regression, which can be used for prediction purposes. In unsupervised learning, only input data is used, and the aim is to identify patterns and groupings in it (Greasley, 2019).

Machine learning is dependent on large amounts of high-quality historical data. The patterns and correlations learned by the models reflect past behaviours and work processes. This means that the predictive capability of the methods presupposes that future conditions will broadly resemble historical ones. Limited data coverage, changing work routines over time, and the relatively low occurrence of fault events can therefore constitute a limitation. Machine learning is most effective when used to support decision-making in environments with high data maturity, where historical observations are assumed to be representative of future operating conditions (Greasley, 2019).

3.3.2 Model-Driven Methods

Model-driven methods use explicit mathematical or physical representations of a system to describe the current state and predict failure development. In the prognostic literature, these methods are often described as physics-based approaches because they rely on knowledge of physics rather than learning patterns only from historical data. A central strength of these methods is that they build on physical understanding, which makes the models more descriptive, improves parameter interpretation, and can reduce errors caused by unexplained or unmodeled phenomena. Model-driven approaches are often costly to implement, require substantial experimental effort, and are typically limited in reuse since they are closely tied to specific systems (Guo et al., 2020).

These methods rely on utilising domain knowledge from individuals who understand how a system works to create a simplified representation, also known as a conceptual model. The underlying mathematical formulations can be divided into static and dynamic models. Static models are fixed in time, which includes spreadsheets, linear programming and simulation techniques. Dynamic models change over time and are used to represent how individual entities move through a system, for example between different resources or by waiting queues (Greasley, 2019).

The complexity of real-world systems makes the abstraction process crucial. It involves making conscious choices about what to include based on the objectives. This is achieved by omission of irrelevant parts, aggregation of processes or replacement of complex behaviours with simpler logic. A guiding principle is that one should always adopt the simplest model capable of explaining a phenomenon (Greasley, 2019).

Simulation is a model-driven method that uses a structured and logic-based representation of how a system works, based on expert knowledge, rules, and resources. This approach enables experimentation with hypothetical or future scenarios, including events that have never occurred. Furthermore, simulations provide explanatory insights into why certain outcomes occur (Greasley, 2019).

Model-driven methods are particularly valuable for managing variability and uncertainty. Simulation enables replacing fixed mean values with statistical distributions, resulting in a more realistic representation of risks. A distinction is made between aleatory uncertainty, which reflects inherent variation within the system, and epistemic uncertainty, which stems from a lack of knowledge about the system's behaviour (Greasley, 2019).

For a model-driven analysis to be valid, thorough verification and validation are required. Verification involves ensuring that the computer-based model accurately reflects the conceptual model. Validation aims to confirm that the model is "sufficiently close" to reality for its intended purpose by testing its conceptual and operational validity, as well as ensuring its plausibility to the decision-maker. It is important to remember that models are simplifications and are therefore never entirely accurate. However, they are powerful tools for explaining behaviour and providing recommendations for the future (Greasley, 2019).

3.3.3 Knowledge-Driven Methods

Knowledge-driven methods are approaches in which domain knowledge is explicitly represented and used in the reasoning process. Rather than relying only on statistical patterns in historical data or physical models, these methods encode what experts already know about a system. The methods work by formalising knowledge so that it can be queried, combined, and applied in a traceable way (Bouhadra and Forest, 2024).

This knowledge can be represented in several forms. One is rule based reasoning, in which knowledge is encoded through formal rules that connect conditions or observations to conclusions (Bouhadra and Forest, 2024). Another is ontology-based representations, where concepts and relations are organised in a semantic structure. This can be done by formalising concepts such as components, failure modes, symptoms and measurements in an ontology that supports reasoning and decision-making (Nuñeza and Borsatob, 2017; Nuñeza and Borsatob, 2018). A further development is the knowledge graph, which maintains the semantic focus of ontologies while representing entities and relations in a more flexible graph structure. It enables representation and management of knowledge to address challenges related to linking information, such as knowledge retrieval and semantic question answering (Sarazin et al., 2021). Across these forms, the principle is that knowledge is made explicit and computationally usable.

Another key feature of knowledge-based methods is that they can reason in a structured and interpretable way even when evidence is incomplete. Thus, the field includes methods for uncertain reasoning rather than being limited to fixed rules. Some approaches used are fuzzy logic, Bayesian networks, and Dempster Shafer theory (Bouhadra and Forest, 2024).

3.4 Models for Fault Prediction

This section presents models for predicting faults in technical systems within the context of predictive maintenance. The aim is to provide an overview of different approaches, how they work, and the requirements they place on data and systems. These models provide support in facilitating a transition from reactive to more proactive maintenance.

3.4.1 Anomaly detection

Anomaly detection is a predictive model in machine learning that identifies deviations in a set of data. The goal of the model is to distinguish between typical and atypical data to detect unusual events or patterns. In artificial intelligence and machine learning, an anomaly is an observation generated by a mechanism that does not normally belong to the data and should therefore be distinguished from statistical outliers (Parimala, 2024). Anomalies can be divided into three categories, one being point anomalies, which is when a single value deviates significantly from the normal values. Contextual anomalies occur when a pattern for a group of data points is only abnormal when viewed in its specific context, and collective anomalies occur when an entire group of data points collectively indicate a deviation in the system (Parimala, 2024).

The model can be of great benefit in predictive maintenance as it can enable proactive solutions and thus prevent crises. It is a common tool used in industry, as continuous monitoring of the system health is essential for ensuring reliable delivery performance. It also enables timely interventions before technical faults develop into major failures or breakdown. Today, the technology is used in water supply, production and maintenance systems to identify and detect technical faults (Parimala, 2024). Today there are a variety of models designed to detect anomalies in real time in complex, multivariate data streams from large numbers of sensors (Parimala, 2024).

However, there are challenges with the technology, including difficulties in obtaining training data for unusual anomalies (Parimala, 2024).

3.4.2 Markov-Based Degradation Model

A Markov-based degradation model is a mathematical method used to assess the reliability and health status of mechanical components by modelling their gradual deterioration over time. The model is particularly useful for complex equipment, where performance inevitably deteriorates due to ageing and wear (Wang et al., 2025).

In a Markov-based degradation model, it is standard practice to use real-time data to determine the condition of the components in the system. In cases where real-time data is not available, a modified version of the Markov-based degradation model, the Degradation Hidden Markov Model (DHMM), can be used instead. Instead of viewing sensor data merely as random observations of a state, the DHMM treats them as part of a time-dependent degradation process (Li et al., 2019).

Linking sensors to a component's health via the DHMM involves creating a mathematical mapping between raw data, such as temperature, pressure and vibrations, and the component's actual condition. In a DHMM, the relationship between the hidden health state and the observable sensor data is defined by an observation matrix. Each element in the matrix specifies the probability that a particular measurement will occur when components are in a specific hidden state, such as "normal" or "anomaly". This is to better handle the uncertainty in sensor readings where a single measurement does not always provide a clear indication of the health status (Li et al., 2019).

A standard Markov-based model assumes that sensor data is stationary, meaning that the mean value for vibrations remains constant as long as the component is in the "normal" state. In DHMM, time-varying parameters are also used, which helps to determine that this is not the case, as wear is an ongoing process (Li et al., 2019).

The model uses normal distributions to interpret sensor data, where each health state is assigned its own ID based on the mean and covariance. The model then uses the Expectation-Maximisation algorithm to learn what these distributions look like for that specific component without the need to set manual alarm limits (Wang et al., 2025).

What is unique to DHMM is the bidirectional link between sensor data and the component's actual health state. The process works by using current measurement data from sensors to calculate and update the probability of which specific hidden state the component is in at a given point in time (Wang et al., 2025). This probability is then used to guide how the model views future developments. Instead of using fixed values, the calculations are adjusted according to a time-dependent degradation rule. If the sensors show a trend of accelerating deterioration, the model will increase the probability that the component is moving towards a poorer state of health as wear accumulates (Li et al., 2019).

3.4.3 Frequency-Based Model Using Historical Information

A frequency-based model using historical information is a statistical, model-driven framework used for predicting extreme values in a data series by combining modern measurements with older historical measurements. Such models are specifically designed to address problems arising from short measurement series, series with many gaps, or when the dataset contains an outlier, an extreme value that causes conventional models to produce unreliable estimates (Hamdi et al., 2019).

The first step in a frequency-based model using historical information is to identify equivalent data sources. To strengthen the basis at a specific target point, the model creates a "homogeneous region" of equivalent data sources. This is done by measuring the asymptotic dependence between different measurement points using a tool known as a spatial extremogram. The aim is to find points that respond similarly to extreme loads or deviations (Hamdi et al., 2019). When data is missing for certain periods at the target point, the model uses multiple linear regression to transfer information from the other points in the homogeneous region. The reconstructed values are then cross validated to ensure they are reliable and to remove measuring stations that do not provide good data. This fills in the gaps and creates a longer and more complete data series, thereby reducing statistical uncertainty (Hamdi et al., 2019).

The model includes information on exceptional events that occurred outside the period during which systematic measurements were taken. This historical data can be retrieved from archives, written records, or documented observations. By adding these values, the sample size is increased, ensuring that even the rarest events are correctly represented in the statistical distribution (Hamdi et al., 2019).

The model uses a statistical calculation method known as Peaks-Over-Threshold with Historical information (POTH). Instead of looking at average values, the method focuses solely on observations that exceed a defined threshold value. POTH uses a mathematical function to combine modern systematic measurements with historical extremes (Hamdi et al., 2019).

3.4.4 Bayesian State Estimation

Bayesian state estimation is a statistical and probabilistic framework used to combine theoretical models with observed data in order to create a more accurate picture of a system’s state. Rather than providing an exact point estimate, the method yields a probability distribution, which makes it possible to manage and quantify uncertainty in complex systems. The Bayesian approach is based on a prior model (initial knowledge) which is then systematically updated with new measurement data to generate an updated picture, known as a posterior (Subramanian and Mahadevan, 2022). In technical applications, this framework is primarily used to reduce epistemic uncertainty, i.e. uncertainty arising from a lack of knowledge about a system’s actual state or flaws in the models describing it. Bayesian approaches can be applied in many ways within predictive maintenance, including state estimation in dynamic systems and probabilistic reliability updating in structural maintenance models (Asgarian et al., 2026; Subramanian and Mahadevan, 2022).

In dynamic systems, Bayesian state estimation is used to identify deviations between a physics-based model and actual measurement data. By representing model errors as additional external inputs in the system’s equations, algorithms such as the Ensemble Kalman Filter can be used to update the system’s state in real time. An important aspect here is the ability to distinguish between transient errors and persistent errors. Transient errors are temporary disturbances that only affect the system for a limited time, whereas persistent errors are long-lasting deviations that continue to affect the system for the remainder of its operation. By identifying persistent errors, one can correct the theoretical model and thereby provide significantly more accurate predictions of the system's future behaviour (Subramanian and Mahadevan, 2022).

Related probabilistic approaches, such as Dynamic Bayesian Networks, are instead commonly used to model degradation and reliability development in physical assets over time (Asgarian et al., 2026). In these frameworks, the condition of a component is continuously updated as new inspection data becomes available, allowing the probability of failure to be revised dynamically. The framework works by integrating fracture mechanics models with inspection results (Asgarian et al., 2026).

When an inspection is carried out, the results are used to update the system's reliability index. If no damage is found, the probability of failure decreases, and reliability "jumps" upwards in the model, if faults are found, one can instead quantify how much the uncertainty decreases and make decisions regarding repairs. By linking this to influence diagrams, decision-makers can optimise the balance between safety and cost-effectiveness. It is then possible to compare different strategies, such as fixed maintenance intervals versus hybrid strategies where inspections are triggered only when reliability falls below a certain threshold (Asgarian et al., 2026).

Despite its great utility, the model also has a number of limitations. The method is often computationally intensive, particularly when complex optimisations are required or when large numbers of simulations are used (Asgarian et al., 2026). The quality of the results is also entirely dependent on the validity of the underlying model. If the laws of physics or the statistical assumptions are incorrect, the update will also be misleading (Asgarian et al., 2026). Furthermore, the framework for a Bayesian approach may struggle to handle overlapping transient errors, where multiple temporary disturbances occur simultaneously and mask one another, making it difficult to isolate the actual cause of a deviation (Subramanian and Mahadevan, 2022).

3.5 Risk-Based Fault Prioritisation using FMEA

Failure Mode and Effects Analysis (FMEA) is a risk management method used for identifying, evaluating and prioritising failure modes in a project, process or system where the goal is to enhance the reliability and safety. The FMEA is a multiple step model starting with investigating and determining the failure modes of the system. Failure modes are faults that can occur in a system and have negative effects on its performance, requiring maintenance actions to restore normal operation (Stamatelatos and Caraballo, 2002).

Once the potential failure modes have been identified, the next step is to assess them based on three criteria, which are Occurrence, Severity and Detectability. In the assessment, all failures are assigned a score on a scale of 1 to 10 (Shafiee and Dinmohammadi, 2014). Occurrence is categorised according to how likely the failure is to occur based on how often it happens. A low number means that the failure is unlikely to occur, whilst a high number indicates a greater likelihood of failure. Severity focuses on the seriousness of the consequences resulting from the fault occurring and is therefore assigned a low score if the consequences of the fault are not considered serious. The final concept examined, Detectability, involves assessing and rating how likely it is that the fault will be detected. It is rated with a low number if the fault is considered easy to detect. Once the three have been assigned a score, the Risk Priority Number (RPN) can be calculated. The RPN is then the number used to determine the fault's position in the prioritisation list. The number is calculated by multiplying the scores for Occurrences, Severity and Detectability according to Equation 1 (Guevara Bastidas et al., 2025).

$$RPN = Occurrence * Severity * Detectability \tag{1}$$

Guevara Bastidas et al. (2025) investigated how FMEA can be used by Operations and Maintenance (O&M) to more easily prioritise which fault should be rectified first in a DH system. In the study, the concept of Detectability is replaced by Monitoring & Maintenance to adapt FMEA to be more useful for O&M. Whereas Detectability in the previous version primarily measured the probability of a fault not being detected before the system fails, the new factor, Monitoring & Maintenance, focuses on faults that may be relevant for O&M to address during ongoing operation, even if the system has not yet failed. To develop a relevant scale for Monitoring & Maintenance, it is divided and assessed based on Monitoring Potential and Maintenance Capability. Monitoring Potential aims to support predictive maintenance by enabling faults to be anticipated before they occur and lead to more serious consequences. Monitoring Potential is assessed based on the type of data and sensors available, for example to detect deviations in temperature, pressure or flow rates. Maintenance Capability is assessed based on the potential for preventing or postponing the fault through proactive measures. Monitoring Potential and Maintenance Capability are each assessed on a scale of 1 to 5. For Monitoring Potential, a low value indicates that there is no possibility of fault detection, a score of 1 means that this is not possible in the current system and could not be achieved even through investment in new components. Maintenance Capability is given a low value, 1, if the fault can only be rectified by replacing the faulty component after it has failed (Guevara Bastidas et al., 2025). The Scales for Monitoring Potential and Maintenance Capability according to Guevara Bastidas et al (2025) is presented in Table 1 and Table 2 respectively. The total Monitoring & Maintenance is then calculated as twice the square root of the product of the two sub-parameters, according to Equation 2.

$$Monitoring \,\&\, Maintenance = 2 * \sqrt{Monitoring * Maintenance} \tag{2}$$

Table 1. Monitoring Potential Scale

Score	Description
5	A change in the component's condition can be detected using existing instrumentation before the fault occurs.
4	A change in condition could have been detected before the fault, but requires additional effort (e.g. new equipment or manual checks).
3	The fault can be detected using existing instrumentation, but only after it has occurred.
2	Detection of the fault requires additional effort and occurs after it has occurred.
1	No fault detection is possible.

Table 2. Maintenance Capability Scale

Score	Description
5	The fault can be prevented by carrying out a quick overhaul or repair before a breakdown occurs.
4	The fault can be prevented by replacing part of the component before a breakdown occurs.
3	The fault can be postponed through appropriate operation (e.g. a change in operating mode).
2	The fault can be rectified through repair after it has occurred.
1	The fault can only be rectified by replacing the entire component after it has failed.

This means that RPN instead becomes the Maintenance Priority Number (MPN), which is calculated by multiplying Occurrence, Severity and Monitoring & Maintenance according to Equation 3 (Guevara Bastidas et al., 2025).

$$MPN = Occurrence * Severity * Monitoring\,\&\,Maintenance \qquad (3)$$

In the study, FMEA is used to place extra focus on how O&M affects the system and the potential for it to influence it (Guevara Bastidas et al., 2025).

4. Methodology

This chapter describes the methodological framework adopted in the study and outlines the design and procedures applied throughout the research process. The chapter presents the research strategy and design used to investigate inspection practices within the DH network in Uppsala. Furthermore, the literature review and methods for data collection are described, followed by the process used for analysing the empirical material. The chapter concludes by addressing ethical considerations and issues related to reliability and validity.

4.1 Research Strategy

The study applies a qualitative research strategy to provide an in-depth understanding of inspection activities, decision-making processes, and the use and interpretation of data within the organisation. Qualitative methods are appropriate for examining context-specific phenomena, especially when the objective is to understand individual experiences and organisational environments (Bell et al., 2019). Inspection and maintenance practices are embedded within organisational routines, procedures, and individual expertise, which are aspects that may not be fully understood from quantitative data. Furthermore, a qualitative approach allows for exploration of how data is perceived, interpreted, and used.

Additionally, the study follows an inductive research approach, where empirical observations form the basis for developing conceptual understanding (Bryman et al., 2025). This approach aligns with the study being exploratory. Rather than testing predetermined hypotheses, the objective is to understand current inspection practices and identify how they could develop towards more predictive, data-driven approaches. There is limited knowledge regarding the current utilisation of inspection data within the organisation, and an inductive strategy enables the identification of patterns appearing from the empirical material (Bryman et al., 2025).

4.2 Research Design

The thesis adopts a case study design to examine inspection and maintenance practices within Vattenfall's DH network in Uppsala. A case study is appropriate when investigating organisational and technical processes in their real-life context (Yin, 2018). Inspection routines are influenced by technical infrastructure and organisational structures, which motivate a broad and context-sensitive research strategy.

The selection of Vattenfall's DH network in Uppsala was strategic. The network is large in scale and has a long operational history, which makes it a relevant case for studying challenges related to ageing infrastructure and evolving maintenance strategies.

The case can be described as an illustrative case, which means that it represents a broader category of similar systems and provides a suitable context for addressing the research questions (Yin, 2009). Maintenance practices in DH networks follow industry-wide standards and constraints, which suggests that the case may offer insights of relevance beyond the specific setting. However, the intention is not statistical generalisation. It should rather be seen as analytical generalisation, where findings are linked to theoretical concepts (Yin, 2018).

4.3 Literature Review

A literature review was conducted to form the background and theoretical framework of the study. The review served three purposes. First, to map existing research on maintenance practices in DH systems and comparable infrastructure. Second, to identify predictive maintenance methodologies. Third, to examine risk-based frameworks for prioritisation and maintenance planning. These areas were used for analysing current practices and opportunities for more predictive approaches.

The search for relevant literature was conducted primarily from Uppsala University's library search tool and Google Scholar. Keywords such as district heating, predictive maintenance, inspections and risk-based maintenance were used in combinations in both English and Swedish. The search process was iterative and continuously refined as new concepts emerged.

Publications were selected based on their relevance to predictive maintenance or structured maintenance approaches. Peer reviewed articles were prioritised as they provide methodological transparency and academic accuracy. Technical reports and industry publications were also used to capture current industry applications.

The review followed a screening process inspired by systematic review principles. After an initial screening of titles and abstracts, selected articles were read in full and thematically categorised (Tranfield et al., 2003). The analysis focused on identifying recurring themes related to data utilisation, decision-making processes, and predictive potential. Key themes then formed the interview guide and the analytical framework used in the empirical phase.

4.4 Data Collection

The empirical material was collected through semi-structured interviews, document analysis, and a supplementary presentation concerning monitoring. The interviews constituted the primary source of empirical material, while the document analysis and presentation were used as complementary sources. These sources provided insight into current inspection practices, maintenance planning, data use, digital systems, and challenges related to the development of predictive maintenance.

4.4.1 Interviews

Semi-structured interviews were conducted with key actors in the DH maintenance organisation in Uppsala as well as with external actors with knowledge of inspection practices and maintenance planning. Semi-structured interviews were chosen as they enable exploration of formal procedures and tacit experiential knowledge. They also allow the researcher to adapt the direction of the interview, ask follow-up questions, and allow respondents to influence the focus of the discussion. This makes it possible to capture what participants themselves perceive as relevant and important (Kvale and Brinkmann, 2009). An overview of the interviews is presented in Table 3.

Table 3. Overview of conducted interviews

Interview	Date	Format	Duration	Main Focus
1	24 Feb	On-site	60 min	Introduction to operations
2	5 Mar	Digital	60 min	Overview and discussion
3	13 Mar	Digital	60 min	Thematic deepening
4	20 Mar	On-site	60 min	Digital systems
5	31 Mar	Digital	60 min	Predictive maintenance and reinvestments
6	11 May	Digital	40 min	Predictive maintenance
7	20 May	Digital	60 min	Comparative perspective on inspection and maintenance practices
8	22 May	Digital	60 min	Comparative perspective on inspection and maintenance practices

The respondents were selected through a purposive sampling strategy, meaning that participants were chosen based on their relevance to the research topic and their knowledge of the studied process (Bryman et al., 2025). The initial interviews focused on the organisation responsible for inspection and maintenance of the DH network in Uppsala. These interviews included respondents with operational and managerial roles, where the aim was to capture how inspection work is planned, carried out, documented, and followed up within the maintenance organisation.

Most of the interviews with Vattenfall were conducted as group interviews, meaning that several respondents participated simultaneously. The purpose of conducting group interviews was to capture complementary perspectives and enable an interactive discussion. As participants are able to respond to and build upon each other's descriptions, the data can become richer (Bryman et al., 2025).

Additional interviews were conducted with respondents outside of the maintenance group. One interview was done with a reinvestment planner working with planning and optimisation, providing insights into how inspections and maintenance need to relate to long-term reinvestment planning. Another interview was carried out with an energy engineer with experience from a previous predictive maintenance project in DH. The purpose was to provide a broader industry perspective on data requirements, predictive modelling, and challenges related to implementation.

In addition, two comparative interviews were conducted with Mälarenergi and Öresundskraft. These interviews were intended to support a comparison between Vattensfall's current practices and those of other DH operators. An overview of respondents and their participation across interviews is provided in Table 4.

Table 4. Overview of respondents and their participation.

Respondent ID	**Department / Organisation**	**Interview participation**
Head of Maintenance	Maintenance & Construction, Vattenfall	1, 3
Technician	Maintenance Uppsala, Vattenfall	1, 2, 3, 4
Project Manager	Maintenance Uppsala, Vattenfall	1, 2, 3, 4
Reinvestment Planner	Planning & Optimization, Vattenfall	5
Energy Engineer	Consultant Energy Systems & Processes, FVB	6
Operations Manager	Mälarenergi	7
Technical Manager	Öresundskraft	8

The interviews were carried out between February and May 2026. Most of the interviews lasted 60 minutes and was conducted either on-site or digitally. Data was documented through notetaking during all interviews, complemented by live transcription when permitted. In addition, audio recordings were used in selected interviews to support the analysis. Both authors participated in all interviews, where one primarily led the discussion, while the other focused on notetaking. Both asked follow-up questions when necessary.

Interview guides with predefined themes were used, but questions were asked in an open-ended manner to encourage detailed responses. The interviews were flexible, allowing deviations from the predefined questions and allowing additional follow-up questions when relevant. This approach is consistent with the principles of semi-structured interviewing, where the interviewer can adapt the conversation while ensuring that key topics are covered (Kvale and Brinkmann, 2009). The interview guide for each interview can be found in Appendix A.

Furthermore, the interview process was iterative. Initial interviews within Vattenfall's organisation provided an overview of the organisation and its practices, which influenced the focus of subsequent interviews. During the analysis, gaps and areas requiring further clarification were identified and explored in later interviews.

4.4.2 Document Analysis

A document analysis was used as a complementary method for data collection. This was done since systematic examination and interpretation of documents can improve the understanding of the study context and provide complementary insights to interview data (Bowen, 2009). The purpose of the document analysis was to support the interpretation of interview findings and give a broader understanding of how inspection work is structured in practice.

The analysed material consisted of operational documents used within the maintenance process, specifically the inspection checklist and fault list related to the inspection process. The checklist was analysed to understand how inspections are structured and documented, including which elements technicians are expected to assess during inspections. The fault list provided insight into how identified issues are categorised and used in planning and prioritisation processes. The documents were analysed alongside the interviews, which allowed comparison between the observations and how respondents described current work methods.

4.5 Data Analysis

The empirical material was analysed with the aim to identify patterns in how inspection and maintenance activities are carried out and how data is used. The analysis focused on converting interview material into meaningful categories related to the study's research questions and theoretical framework.

The first stage involved a thorough review of all collected data. Interview notes and transcriptions were read multiple times to become familiar with the content and identify recurring topics. This step allows the researcher to gain an overall understanding of the data before diving into more detailed interpretation (Braun and Clarke, 2006). Focus was directed towards descriptions of inspection routines, decision-making processes, data usage, and perceived challenges in current working methods.

Next, the material was systematically coded. Segments of the data were labelled based on their content to capture important aspects of the respondents' descriptions. This helps identify patterns that can later be expanded into larger analytical categories (Saldaña, 2013). The coding process was linked to the empirical material, which allowed relevant categories to emerge from the data. The analysis was also guided by concepts related to maintenance strategies, data use, and predictive approaches. This helped focus the interpretation on aspects relevant to the study's purpose.

The codes were then grouped into broader themes representing central aspects of the studied process. The goal was to identify and describe patterns and relationships within the empirical material. For instance, descriptions of inspection intervals and classification systems were grouped into themes reflecting time-based maintenance structures. Observations about digital tools and documentation practices were grouped into themes related to data availability and system integration. Developing such themes helps organise qualitative data into meaningful analytical structures and allows for interpretive analysis of the data (Braun and Clarke, 2006). The themes were then refined and structured in relation to the research questions. This led to categories that form the basis of the analysis chapter.

4.6 Ethical Considerations

Ethical considerations are important in the research process, particularly in qualitative studies where data are generated through interaction with participants (Arifin, 2019). In this study, ethical principles were addressed from the initial design to data collection and analysis. The study follows the principles of good research practice outlined by the Swedish Research Council. These principles emphasises that ethical responsibility goes beyond simply following rules, it also includes continuous reflection on how research is conducted in practice (The Swedish Research Council, 2024).

An ethical requirement is informed consent. Interview participants received clear information about the study's purpose and how the data would be used. Following established research ethics, participation was voluntary, and respondents were informed that they could withdraw at any time. Informed consent is important for ensuring that participants can make well-informed decisions about their involvement (Bell et al., 2019). This aligns with the principles highlighted by the Swedish Research Councils, where respect for individuals and their autonomy is an important aspect of good research practice (The Swedish Research Council, 2024).

Confidentiality and anonymity were also prioritised during the study. Since qualitative interviews may include personal experiences and organisational insights, protecting participant identities is important. This involves careful management of information to ensure that individuals cannot be identified without their consent (The Swedish

Research Council, 2024). All respondents were therefore given coded identifiers, and identifying details were either removed or generalised when presenting the findings.

The organisational context of this study creates additional ethical considerations, particularly regarding power dynamics. Participants might feel pressure from their employers or hesitate to express critical opinions. To address this, it was communicated that the participation was voluntary and independent of organisational authority. Additionally, no individual responses were shared with the organisation, and all data were kept confidential. This approach reflects the broader ethical principle of minimising harm and protecting participants from possible negative outcomes (Bell et al., 2019).

Data management has also been conducted in accordance with principles of responsible research practice. Responsible data management includes secure storage, controlled access, and proper handling throughout the research process. This helps protect the integrity of research participants (The Swedish Research Council, 2024). Interview recordings, notes, and transcripts were securely stored in a meeting documentation system with restricted access, only allowing access to the authors or participants involved in the respective meetings. Personal data were handled carefully, used solely for research purposes.

4.7 Reliability and Validity

In qualitative research, reliability and validity implies how well the research process is conducted and whether the study captures what it aims to explore. Reliability is often linked to the consistency and stability of the research process, while validity concerns whether the chosen methods address the research aim (Bryman, 2016).

Regarding reliability, this study focused on maintaining a consistent and transparent research process. The interview guides offered a common framework across interviews, ensuring that similar topics were discussed with all participants and that all topics necessary were covered. Another factor that affects reliability is the role of researchers. Since qualitative research involves interpretation, the way questions are asked and how answers are understood can be influenced by the researchers' viewpoints. To address this, the data was reviewed multiple times during analysis, which helped create a more consistent interpretation of the material.

Validity can be associated with how the interview questions were developed and used during data collection. The questions were created with the research purpose in mind and organised around central themes such as inspection practices, data usage, and maintenance processes. This connection increases the likelihood of the data being relevant to the research questions. This can be seen as improving the study's validity. Additionally, using semi-structured interviews allowed for adjustments to the questions during the interviews. This flexibility enabled follow-up questions and clarifications, helping to ensure that participants' answers reflected what the study intended to explore. Such flexibility can improve validity in qualitative research since it allows the researcher to explore emerging topics in greater depths. However, there are limitations worth considering. One aspect is that the interview guides were not tested before the data collection began. Piloting can help catch unclear wording or unintended interpretations (Bell, 2014). Without this step, some questions may have been understood differently by participants than intended. Although clarifications were made during the interviews as needed, it cannot be fully guaranteed that all respondents interpreted the questions the same way.

Furthermore, since interviews are interactive, meaning is shaped through the conversation. There are differences in experience and perspective that can affect how questions are understood (Bryman, 2016). To minimise this risk, the questions were created in a clear and straightforward way. In addition, follow-up questions were asked to confirm and clarify participants' answers when necessary.

5. Empirical Findings

This section presents the empirical basis for the study, which was gathered through interviews. The empirical data aims to describe how inspection and maintenance work is carried out in practice, focusing on work processes, digital systems, decision-making, and perceived challenges and limitations in the current working methods.

5.1 Inspection Planning

The inspections are planned to start every year around March, depending on weather conditions and traffic-related constraints (Project Manager, 2026a). The timing of inspections is therefore partly seasonal, as fieldwork in chambers and road environments becomes difficult during periods of heavy snow or poor accessibility (Technician, 2026b).

The chambers in the network are divided into three different classification groups, which are A, B and O. The classification is based on the criticality of the chamber and the potential consequences of a fault. Chambers connected to pipes with diameters larger than DN 350 are classified as A objects and are considered to have greater consequences in the event of a failure. B (DN 250-300) and O classified chambers are generally connected to smaller pipes and are therefore considered to have less severe consequences if faults occur. A classified chambers are inspected yearly while B and O classified chambers are inspected every other year (Project Manager, 2026a).

Inspection work is thus largely governed by fixed time intervals rather than condition-based prioritisation. All assets are scheduled for inspection within the same temporal cycle, regardless of their condition or known defects. As a result, assets with known issues are not necessarily prioritised over others within the inspection routine (Technician, 2026b).

In addition to time-based inspection planning described by the maintenance organisation, a respondent working with planning and optimisation describes how inspection and maintenance activities are also connected to broader reinvestment planning. From this perspective, the organisation follows a principle where assets should be used as long as they remain functional and meet safety requirements. Planning includes long-term considerations regarding maintenance backlog, reinvestment needs and cost efficiency. A respondent describes that maintenance and reinvestment needs are evaluated with a planning horizon of approximately one to two years, where different needs are assessed and prioritised in relation to available resources and planned projects (Reinvestment Planner, 2026).

The respondents describe the Uppsala networks as a large network with clear procedures. They also state that there is a maintenance manual for the DH network, which serves as a general guideline for inspection and maintenance practices across the country. However, there is uncertainty regarding how close Vattenfall's current practices align with procedures used in other DH networks. Over time, there have been different approaches added and adapted to the Uppsala DH inspections, making it hard for the technicians to say how closely aligned todays work is to the manual. (Technician, 2026a).

5.2 Inspection Practices

The practical inspection work is carried out by technicians in the field. The technicians first decide in which geographical area to start. They use Utility To Go (UTG), a digital tool used on tablets in field, to locate chambers in the determined area. UTG is also used to access the inspection checklist, document observations and register faults that require follow-up or later corrective action. Minor maintenance tasks that can be completed directly during the inspection are handled on site (Technician, 2026b).

During the inspection of a selected chamber, the checklist in UTG is used to ensure that required inspection elements are reviewed and documented (Technician, 2026b). The checklist is organised as a questionnaire and covers several inspection elements, including corrosion of pipes, leakage around fixtures, insulation condition, accessibility, work environment, ventilation, presence of alarms and cleaning. For each element the technician selects a limited set of predefined response options, such as "Yes", "No", "Ok", or "Not relevant". In addition, the system allows the technician to add short free-text comments when further clarification is needed (Vattenfall AB, 2026b).

The inspection itself is often relatively quick. However, surrounding preparatory activities can make the overall process more time-consuming. For example, deeper chambers require fall protection, which extends preparation time (Head of Maintenance, 2026). Setting up equipment such as tripods may in some cases take longer than the inspection itself, particularly when no significant issues are identified (Technician, 2026c). The time required for each inspection also varies depending on the physical configuration of the chamber. Some chambers contain few components and are easy to assess, while others are more congested and require more extensive work due to limited accessibility or a larger amount of installed equipment (Technician, 2026c).

Inspection work in street environments also creates administrative and practical constraints. When inspection activities require road access, traffic management plans must usually be submitted and approved by the municipality before work can begin. In acute cases, excavations may be initiated before approval is granted, with documentation submitted retrospectively (Project Manager, 2026c).

Although UTG is the main tool for documenting inspection results, not all activities carried out in practice are necessarily reported in the system. For example, if a chamber has required pumping repeatedly over a short period of time, these repeated interventions may not be documented individually (Technician, 2026c).

5.2.1 Condition Assessments and Evaluation Practices

Condition assessments during inspections are inherently interpretative. Although structured protocols are used, including binary and graded responses options, respondents describe how evaluations depend on individual judgement. This applies, for example, to how technicians evaluate corrosion, structural cracks, or material degradation, and whether they physically probe surfaces or rely on visual inspection alone (Technician, 2026b).

Many checklist questions rely on broad, categorical response options without specified quantitative thresholds, resulting in aggregated descriptions of conditions such as corrosion, insulation status or accessibility. More detailed information about the inspection circumstances is instead mainly documented through free-text comments. These comments provide valuable contextual information, but they also vary in level of detail, wording, and interpretation across inspections, even when similar physical conditions are being described (Vattenfall AB, 2026c).

Another example of condition assessment concerns the difficulty of interpreting visible signs of deterioration. Respondents describe situations where components have been repainted despite underlying corrosion, particularly for elements located in low-lying areas that may have been exposed to water. In such cases components may appear to be in acceptable condition, while testing may reveal leakage or remaining deterioration beneath the surface (Technician, 2026c).

Attempts have been made to standardise assessment practices through manuals or joint calibration exercises. However, these attempts are described as difficult to implement in practice. Attempts to develop a manual for standardising assessments were challenging, since translating judgement into usable guidance proved to be almost as difficult as the assessment process itself. Comparison exercises also showed that technicians interpret identical conditions differently (Technician, 2026c). Participants conclude that subjectivity is inevitable, although the reporting protocol's severity categories offer a minimal shared framework (Technician, 2026c; Project Manager, 2026c).

5.3 Operational Digital Systems

Operations and maintenance work within the DH network is partly supported by several digital systems used for inspection, monitoring, documentation and maintenance planning. These systems are used at different stages of the operational workflow, from field inspections to fault registration and alarm handling. However, respondents describe that the systems are not fully integrated, meaning that information is not automatically exchanged between them.

Trimble NIS is the main digital system in which information about the distribution network is stored. It contains information about the location and characteristics of pipelines, chambers and ground valves. Each chamber is registered with a unique chamber number, which is used to identify the chamber across operational systems and in communication during maintenance work. UTG can be understood as the maintenance-oriented field component of Trimble NIS and is used by technicians during inspections through tablets in the field (Technician, 2026b).

In UTG, users can access information about induvial objects in the network. For example, by opening a specific chamber, it is possible to view previous maintenance activities and measures related to that chamber, such as whether it has required pumping or whether rusty pipes have been painted (Project Manager, 2026d). However, compiled historical maintenance data for all components in the system is not available. Respondents also describe that the available history for each component is also not utilised as part of the process (Technician, 2026d).

UTG is also used to document inspection results. When technicians identify an issue during inspection and select the relevant option in the checklist, the information is transferred to another part of Trimble NIS. There, the reported issues are compiled into a fault list containing identified faults in the network. This serves as a tool for identifying faults in the network and for facilitating the management and rectification of these faults (Project Manager, 2026b).

Pipeguard is used as a monitoring system for chamber alarms in the DH network. In the current set-up, alarms are only triggered for critical water levels in chambers (Technician, 2026b). Beyond its current use in Uppsala's chambers, Pipeguard also has potential for broader condition monitoring. The system can handle additional types of continuous measurement data, including temperature, pressure and humidity in the chambers. To utilise this information, the data must be exported from Pipeguard (Pipeguard Manager, 2026).

5.4 Critical Events and Emergency Response

In addition to planned inspections, the maintenance organisation also manages acute operational events that require immediate response. The presence of water inside a chamber is considered critical regardless of its origin. Water may originate from leaking pipes, snowmelt, rainfall, or intrusion from adjacent culverts, and must be removed without delay (Technician, 2026c). Rapid removal of water is important because prolonged moisture exposure can accelerate deterioration and create further problems in connected parts of the systems (Energy Engineer, 2026).

When a chamber alarm is triggered due to rising water levels, an SMS is sent to a technician on call. The message includes the chamber number and a statement that a critical water level has been reached. If the technician is unfamiliar with the chamber's location, UTG is used to identify its position. The initial response is always to travel to the site and assess the situation. At this stage, it is not known whether the water originates from leakage or not, and the cause must therefore be determined on-site before appropriate measures can be taken. The first measure typically involves pumping out accumulated water, after which further investigation is carried out to determine the source and severity of the issue (Technician, 2026c). For safety reasons, work inside chambers is not conducted by a single technician. If entry into a chamber is required, a second technician must be present (Head of Maintenance, 2026). Initial assessments are therefore made from above ground, with additional personnel called in if a closer inspection or work inside the chamber is necessary (Technician, 2026c).

Although all occurrences of water are treated seriously, the operational team differentiates between immediately hazardous situations and those that can be temporarily stabilised (Technician, 2026c). Severe incidents, such as major ruptures or breaks in main distribution pipes, may require immediate excavation, isolation, and potential sectioning of the network (Project Manager, 2026c). In contrast, minor leakages can often be managed through repeated pumping over an extended period, ranging from days to weeks, until an excavation can be scheduled without causing unacceptable service disruptions (Technician, 2026c).

The criticality of a fault is not determined solely by its technical characteristics, but also by its spatial and social context. Several respondents emphasise that similar leakages may be handled differently depending on their location. For example, a leakage located in a remote green area may be temporarily managed, whereas a similar leakage in a densely populated residential area or near locations such as school routes or playgrounds require more immediate action (Project Manager, 2026c).

The time required to address a leakage varies depending on how difficult it is to locate and access the source. Respondents describe that leakages may be difficult to identify and reach due to surrounding infrastructure, as well as the need to perform complex network isolations before excavation can be initiated (Technician, 2026c).

Leakage management is further characterised by a continuous balancing between immediate intervention and planned maintenance. In many cases, temporary measures such as installing a clamp, are used to seal the pipe and stabilise the situation. This enables continued operation while allowing the repair to be incorporated into a larger maintenance project rather than being addressed separately. This approach is dependent on the leakage remaining controlled and not posing immediate risks (Technician, 2026c).

Access to on-call welding and excavation resources allows for rapid intervention when necessary, particularly in situations involving damage to property or risks to public safety. Conversely, if the leakage can be contained, through pumping or controlled discharge, and does not directly affect customers or safety, intervention may be postponed in favour of more strategic planning (Technician, 2026c).

Alarm systems are not installed in all chambers, but primarily in those considered more critical. As a result, an alarm may be triggered in one location while multiple connected chambers are already filled with water, as water can spread through the network and accumulate across interconnected chambers (Technician, 2026b).

Respondents describe false alarms from chambers as rare, with only occasional incidents caused by snakes or rodents activating the physical float switches. In contrast, false negatives in the alarm system, meaning that alarms are not generated or transmitted at all, are described as a more significant issue. They may occur due to damaged antennas, for example because of ploughing or vandalism, as well as malfunctioning alarm switches that prevent triggering or transmission of SMS notifications. Additionally, false negatives can result from configuration errors, such as failing to activate the SMS notification function during installation. The technician reports instances where chambers were found flooded during routine inspections without any prior alarm notification (Technician, 2026c).

5.5 Fault Handling and Prioritisation

Faults identified during inspections are compiled in a fault list generated in NIS. It is used by the project manager to review reported issues, determine which measures are needed, as well as to prioritise and plan the necessary actions (Project Manager, 2026b). The list can be sorted by chamber, component or fault type. This allows the project manager to identify patterns across the network, such as several chambers requiring the same type of measure or recurring issue related to specific components. This sorting can also be used to identify whether larger-scale campaigns can be carried out, for example to replace multiple ladders at once (Project Manager, 2026b).

Because the number of faults exceed the available time and budget, a prioritisation process is required. This is carried out manually by the project manager, who reviews the list and assess which faults require action first and which can be postponed. This is determined by several factors such as urgency, safety risks, operational consequences, cost, and practical feasibility (Project Manager, 2026b).

A fault that poses a direct safety risk or operational disruption is generally prioritised (Project Manager, 2026b). At the same time, respondents describe that cheaper and simpler measures are generally prioritised to resolve many issues within the available budget. This may involve replacing signs or carrying out minor anti-corrosion painting. More complex and costly measures usually end up at the bottom of the list, as these measures typically require more planning and greater coordination within Vattenfall (Project Manager, 2026b).

The cost and time required to address a fault may vary considerably depending on the type of measure and the surrounding conditions. Some measures are relatively easy to estimate, particularly when they do not require excavation or approval from external actors. In contrast, measures requiring excavation or road access are usually more expensive and time-consuming. When work affects roads, a traffic management plan must be developed and approved by the municipality, which can delay corrective actions (Project Manager, 2026b).

Prioritisation is not based solely on the technical severity of a fault. It is also shaped by practical constraints, such as accessibility, required permits, available resources, and the possibility of coordinating several measures within the same project. This makes it difficult to establish a standardised method for determining how faults should be prioritised, since the same type of fault may require different levels of effort depending on its location and context (Project Manager, 2026b).

Coordination with other departments working on network improvements is therefore an important part of fault handling. Respondents describe that regular communication is needed to avoid duplicating work, ensure that maintenance measures are aligned with other planned network improvements and to save money by combining several measures into the same project. Without regular coordination, there is a risk that time and budget will be spent on repairing components in a chamber that is already planned for replacement or renovation by another department (Project Manager, 2026d).

Vattenfall is also in constant communication with the municipality, as work on the DH network must be aligned with urban development plans. Planned municipal infrastructure projects affects Vattenfall's ability to prioritise its own measures (Technician, 2026d). For example, if new residential development is planned in an area within the coming years, larger renovation of nearby pipes and chambers may be postponed so that they can be coordinated with the municipality's future construction work (Technician, 2026d).

5.6 Insights from Previous Predictive Maintenance Project

One of the interviews provided insights from a previous industry project that attempted to develop a predictive platform for localising faults in a DH network. The initial goal was to develop predictive models capable of identifying high-risk areas within DH networks. A range risk factor was initially considered as potential input variables, including pipe age, type, dimension, and external conditions. However, due to constraints in data access and usability, the scope was gradually reduced. In practice, the analysis relied mainly on historical leakage data, which limited the depth of the analysis and the possibilities to incorporate additional explanatory variables (Energy Engineer, 2026).

A limitation of the project was related to data availability and the ability to use existing data. Although relevant data existed within organisations, several constraints restricted its use. One challenge was related to information security. It was not possible to link failures to specific geographical locations or individual chambers, as this was considered sensitive information. In addition, important types of condition data, such as water levels and humidity in chambers, were either not systematically collected or could not be connected to failure events (Energy Engineer, 2026).

The project also highlighted several organisational challenges related to data collection and usage. Documentation practices are described as inconsistent, and important information was not always recorded or stored in a structured way. Field personnel tend to prioritise immediate problem solving, which can result in limited reporting and incomplete data. Furthermore, data from completed projects is not always preserved in a way that makes it accessible for future analysis (Energy Engineer, 2026).

The project resulted in the identification of several factors associated with failures. These factors were consistent with existing operational knowledge. However, due to the limited dataset, the analysis mainly confirmed previous known relationships rather than providing new or more detailed insights (Energy Engineer, 2026).

In contrast to the limitations identified in the project, there are examples within the industry where more extensive measurements practices have been implemented. One such case involves a company that performs continuous, real-time monitoring of conditions within chambers. This includes measurements of parameters such as temperature and humidity, which are recorded continuously over time. The data is used to analyse how conditions change and to identify patterns associated with failures (Energy Engineer, 2026).

Rather than relying on advanced data-driven models, the organisation applies a more knowledge-based approach, where measured data is interpreted using experience and understanding the failure mechanisms. By analysing how measured parameters change prior to known failures, the organisation has in some cases been able to identify patterns that allow for earlier intervention (Energy Engineer, 2026)

5.7 Findings from Comparative Companies

This section presents empirical findings from interviews with representatives from Mälarenergi and Öresundskraft. The purpose of these interviews was to provide a comparative perspective by relating Vattenfall's current inspection routines, digital systems, data use and approaches to predictive maintenance to practices in other DH networks. Both organisations operate networks that include older infrastructure as well as newer technical solutions.

The findings show that the basic inspection and maintenance logic is broadly similar across Vattenfall, Mälarenergi and Öresundskraft. In all three organisations, physical inspections, operational follow-up and fault handling remain important parts of the maintenance process. However, the organisations differ in how far they have developed digital integration, sensor-based monitoring and structured use of data in maintenance planning.

5.7.1 Inspection and Maintenance Workflow

At Mälarenergi, inspection and maintenance activities are carried out through a structured workflow in which inspections, fault identification, and maintenance activities are connected (Operations Manager, 2026). Inspections are performed by internal personnel. One person has the primary responsibility for an inspection, but the work is carried out in collaboration with other technicians who are also involved in operational tasks. According to the respondent, this contributes to a more realistic understanding of working conditions in the network (Operations Manager, 2026).

The inspections are conducted using structured checklists with predefined inspection elements. The checklist consists of headings and instructions describing what should be assessed and which symptoms to observe. Identified issues may come from several sources, including planned inspections, alarms, customer reports and thermographic inspections. These observations are recorded and categorised within the system based on their origin and characteristics (Operations Manager, 2026).

The respondent also describes that previous work practices sometimes resulted in repeated visits to the same locations for different inspection tasks within the same period. In response, efforts have been made to coordinate inspection activities and consolidate tasks to reduce multiple visits to the same site (Operations Manager, 2026).

Öresundskraft describes a similar general inspection logic as Vattenfall. Their inspection work is also based on physical inspections of chambers, where operational issues such as water ingress and pump operations are handled as part of routine maintenance. An operational team is responsible for monitoring daily conditions in the network, including water in chambers and pump-related activities (Technical Manager, 2026).

5.7.2 Digital Systems and Fault Prioritisation

Mälarenergi uses Trimble NIS to manage spatial and asset-related information in the DH network. In addition, other digital tools are used to support monitoring, alarms and visualisation of operational data (Operations Manager, 2026).

A central organisational change highlighted was the transition from using UTG for maintenance management to using their enterprise system. In the previous system configuration, faults and maintenance activities were managed through a list that was not directly integrated with work execution. This resulted in an extensive fault list and required the involvement of specific individuals to retrieve and manage information. Faults could remain in the system even after they had been addressed, and the list became difficult to rely on over time. In some cases, maintenance actions were initiated based on outdated information, resulting in inefficiencies (Operations Manager, 2026).

Following the system transition, fault reporting, work orders, and maintenance activities are handled within a more integrated workflow. Identified faults can be converted into work orders, which creates a clearer connection between inspection outcomes and maintenance actions. The system also provides users with an overview of ongoing inspections, assigned tasks, process flows, and completed actions. The respondent also describes the use of work packages to improve efficiency. Similar tasks may be grouped together, for example when they require the same type of equipment or external contractor (Operations Manager, 2026).

Faults and observations are categorised according to their urgency using a structured classification system. The respondent describes three principal categories. Category A refers to critical issues that should be addressed within a year. Category B refers to issues that should be addressed before the next scheduled inspection. Category C refers to non-critical observation that do not affect operation but should be monitored over time (Operations Manager, 2026).

Öresundskraft is developing an internal decision-support system linked to a GIS platform. The aim is to combine and analyse data from several sources in one system. Measurement points can be visualised geographically, and users can filter and display specific parameters such as humidity or the parameter referred to by the respondent as delta t, which relates to pipe wall thickness (Technical Manager, 2026).

5.7.3 Sensor-Based Monitoring and Condition Data

At Mälarenergi, alarm systems are used to monitor water levels in chambers. The respondent describes that daily meetings are held within the operations team to review active alarms and determine necessary actions. When alarms are triggered, technicians are dispatched to inspect and carry out measures such as pumping out water. These activities are documented within the system and can be followed over time. The system also enables tracking of recurring events, such as repeated pumping in specific chambers (Operations Manager, 2026).

Öresundskraft has installed sensor units in all chambers within the network. Larger chambers are equipped with a more advanced sensor unit, referred to as a smart active box. These are mounted inside the chambers and measure several parameters continuously, including temperature, water levels, humidity and delta t. Smaller chambers are equipped with simpler sensor units that mainly measure temperature, humidity and water levels (Technical Manager, 2026).

The respondent describes delta t as a central parameter in their work with monitoring. The respondent also stated that current efforts are strongly focused on monitoring humidity levels in chambers. Humidity levels above approximately 60% are described as important, as they may indicate a corrosive environment and potential water ingress (Technical Manager, 2026).

5.7.4 Data Use and Predictive Maintenance

At Mälarenergi, data is collected through inspections, alarms and maintenance activities. This includes information about faults, interventions, and operational events such as pumping frequency. Different types of aggregated data are available, including information on ongoing leakages, pumping activity, and maintenance history. Historical data is used in specific contexts, particularly for reinvestment planning. However, the respondent notes that historical data is not systematically used in the planning of inspection activities (Operations Manager, 2026).

The respondent highlights challenges related to combining information from different sources. The respondent emphasises that meaningful insights often require connecting several datasets. It is also noted that although data is available, it is not always clear which parameters should be used to assess the condition of the network or indicate future risk (Operations Manager, 2026).

Predictive maintenance is an area of ongoing discussion within the organisation. A central challenge is identifying data that can reliably indicate when components are approaching failure. Existing measurements are described as useful, but not sufficient to provide a complete understanding of system condition. The respondent also notes that measurements are not always available at the most critical locations in the network (Operations Manager, 2026).

Questions regarding the balance between cost and benefit is also raised, particularly whether the value of predicting failures justifies the associated costs. At the same time, emphasis is placed on the importance of ongoing maintenance activities, including smaller interventions that can be carried out continuously and contribute to overall functioning of the network (Operations Manager, 2026).

Öresundskraft's ambition is to collect a large amount of data and integrate different data sources into a unified system. According to the respondent, the aim is to enable a more predictive approach, for example in decisions regarding when pipelines should be replaced (Technical Manager, 2026).

Economic considerations are described as an important driver in Öresundskraft's work with data-driven maintenance. A major leakage event, which resulted in significant costs, is described as one factor that motivated further development and investment in monitoring systems. The respondent states that these investments have been evaluated through business case analyses. It is also described that the organisation has saved money through this approach (Technical Manager, 2026).

The respondent also mentions several challenges related to data-driven and predictive maintenance. While some data is collected automatically through sensors, other information relies on manual input from technicians. The usefulness of the overall system depends on the quality of the input data. For example, the respondent notes that it is possible to mark conditions as "OK" with limited detail when entering data. This affects how the data can later be used in analysis and decision-making (Öresund). The respondent further describes that the large amount of collected data creates a need to identify which parameters are most relevant within their approach to predictive maintenance (Technical Manager, 2026).

6. Analysis and Discussion

In this chapter, the empirical findings are analysed and discussed in relation to the theoretical framework. The discussion focuses on how inspections are organised, how data is collected and used, how maintenance decisions are made, and which predictive methods appear most suitable given the current organisational and technical conditions. Furthermore, the chapter identifies both existing limitations and potential development paths. The chapter concludes by discussing organisational and strategic implications for implementing a more structured and forward-looking maintenance framework.

6.1 Current Inspection and Maintenance Practices in Relation to Predictive Maintenance

The empirical findings demonstrate that inspection and maintenance practices regarding chambers within Vattenfall's DH network in Uppsala are primarily grounded in time-based and reactive maintenance logics. Although elements of condition awareness and digital support are present, the overall inspection regime remains structured around predefined inspection intervals and manual prioritisation, with limited systematic use of historical or condition-based data to inform maintenance decisions beyond the immediate inspection context.

Inspections are planned yearly and organised according to a classification depending on the chamber's perceived criticality, which determines the inspection frequency. While this approach reflects an attempt to acknowledge risk and consequences to some level, it remains primarily static. The classification does not dynamically adapt to emerging degradation patterns, repeated faults or changes in component condition over time. As a result, assets with known reoccurring issues are not prioritised within the inspection schedule, which aligns with characteristics of preventive rather than predictive maintenance.

From a theoretical perspective, predictive maintenance is characterised by the anticipation of failure based on trends, condition indicators and historical performance data, enabling interventions to be performed just before failure is likely to occur. In contrast, the inspection practices rely on regular physical assessments regardless of prior inspection outcomes. This is consistent with previous studies of DH systems, which describe how maintenance practices are often characterised by strong reliance on established routines and predefines intervals, while the systematic use of condition data and historical information for predictive decision-making remains limited.

6.2 Data Availability, Data Quality and System Integration

The empirical findings show that the organisation collects and stores several types of data that are relevant for maintenance planning in the DH network. Inspection data, fault lists, object information, historical notes and alarm data all exist within the digital environment. However, a limitation is how the data is structured and used. The current practices support documentation, operational response and administrative follow-up, but it does not provide a sufficiently integrated basis for predictive maintenance. Predictive maintenance depends on the collection of large volumes of data, and on the data being of sufficient quality that can be combined across different system levels and transformed into decision-supporting information.

Several digital systems are used in the inspection process, each contributing different types of information. These systems create a digital infrastructure for inspection and maintenance work. However, the systems are not fully integrated, and information does not automatically flow between them. This means that data must be interpreted, transferred or used manually rather than being combined into a coherent decision-support structure.

At the inspection level, UTG enables technicians to document observations, complete checklists and report faults. These reported faults then appear in Trimble NIS, where they are used to generate a fault list for further planning and prioritisation. This creates a functional link between inspection and fault handling. However, the link remains primarily administrative. It helps the organisation identify and manage observed faults, but it does not support analysis of how faults develop over time, how often specific conditions reoccur, or whether certain chambers show signs of degradation.

Pipeguard provides sensor-based information. However, this data is mainly used for acute action, rather than for long-term analysis. Data from Pipeguard is therefore valuable from an operational perspective, but its predictive potential remains limited if it is not systematically linked to inspection records, previous maintenance measures and history.

In addition to its current use, Pipeguard also has the technical capability to handle a wider range of continuous measurements within the chambers. This means that the system could have provided a more detailed and continuous picture of the condition of the components, rather than simply triggering an alarm in the event of high water levels. By collecting this type of data over time, it would be possible to identify gradual changes and patterns in component behaviour, such as increased moisture levels or abnormal temperature trends, which may indicate accelerated degradation. This type of continuous measurement is important to the development of predictive maintenance, as it enables the analysis of trends. By linking this type of measurement data to historical inspection data and actions taken, Vattenfall could gain a better understanding of how different types of faults arise and how they develop over time under various conditions. This mean that they could use this data to identify the start of potential faults earlier, prioritise maintenance and optimise the timing of maintenance work.

The current situation indicates a gap between data collection and data utilisation. Parts of the data infrastructure are in place, where sensors, inspections and operational systems generate observations about the chambers. However, the process required to integrate, analyse and transform this information into decision support, remain underdeveloped. This can be related to the system pyramid, where data from sensors and physical assets form the foundation, which is linked to operational systems and further to overarching decision-making and planning systems at higher levels. Only when data can flow vertically between these levels are the conditions created for predictive analyses that support long-term planning and proactive maintenance decisions. Currently, the lower levels exist to some extent, but the vertical connection between them is limited.

This limitation is particularly visible in relation to historical information. Compiled historical data for all components is not available, and the history that exists is not used in the maintenance planning processes. This means that historical information remains local and object-specific rather than being transformed into aggregated knowledge about the network.

The lack of integration also affects the possibility of identifying recurring patterns. For example, the fault list can be sorted which allows certain recurring issues across different chambers to be identified manually. This can support practical planning such as grouping similar measures into larger campaigns. At the same time, this form of analysis is still dependent on manual interpretation and does not constitute predictive analysis in a more advanced sense. The system may help identify that a problem has occurred repeatedly, but it does not automatically estimate whether the risk is increasing, whether a particular fault combination is significant, or if certain chambers should be inspected earlier than planned.

This limitation becomes especially clear when compared with other actors in the industry. Currently, Vattenfall's digital tools primarily function as standalone units where the link between inspection and fault management remains largely administrative and manual. This contrasts with the experience of Mälarenergi, which has implemented a strategic transition from a solution similar to Vattenfall's current one to a more integrated business system. By linking fault reporting directly to the generation of work orders, they have created a more integrated workflow that reduces the reliance on specific individuals interpreting or transferring information manually. For Vattenfall, the absence of such integration increases the risk of inefficiency.

The empirical findings concerning a previous predictive maintenance project illustrates that data availability does not always mean that the data is suitable for prediction. In that project, data could not always be linked to specific geographical locations, which reduced the possibility of analysing spatial patterns, whilst the absence of parameters limited the model´s level of detail. In addition, relevant parameters were not always systematically recorded, limiting the level of detail in the model and reduced its practical usefulness. This is important since DH network failures are influenced by local conditions. Chamber condition, water exposure, traffic load, surrounding infrastructure and more may all affect degradation. If such factors are not recorded in a structured and linkable format, the organisation cannot analyse how they interact. Predictive maintenance in this context therefore requires not only more data, but more contextually meaningful data.

The lack of vertical system integration is reflected in the system pyramid, where the upper level, in which data is transformed into decision-making input and predictive insights, remains underdeveloped. Although several relevant data sources already exist, the potential for predictive maintenance is not being utilised. In practice, this indicates that the data primarily supports reactive and descriptive working methods, where actions are initiated in response to alarms, visible faults or manual assessments, rather than through analyses of long-term patterns and future risks.

To complete the pyramid and enable predictive maintenance, what is required is measures that strengthen vertical integration. This means that links must be established between Sensors/Actuators, DCS/PLC and SCADA and MES so that sensor data can be related to inspection observations, previous actions and component history. For example, sensor data should be systematically linked to specific chambers and components, with measurement data stored with time stamps and connected to corresponding inspection object. This would make it easier to relate sensor data to inspection observations, previous maintenance actions and component history. Furthermore, the MES level needs to evolve towards more standardised and structured data collection that enables analysis over time. Finally, a clearer link is required between MES and ERP, where condition and inspection data are systematically used as a basis for strategic decisions regarding prioritisation, resources and long-term asset management. Without these links, the system pyramid remains incomplete, limiting the ability to move from reactive and descriptive working methods to more predictive and proactive maintenance.

One difference that highlights Vattenfall's need for increased data generation is the extent of sensor coverage across the network. Whilst Vattenfall currently relies primarily on alarms for critical water levels in selected, priority chambers, Öresundskraft has installed more advanced sensor units in all chambers within the network. The volume and range of data generated means that they carry out a high degree of condition monitoring, enabling the analysis of long-term trends rather than just responses to acute events.

For Vattenfall, this comparison helps to underline the importance of generating more contextually meaningful data to identify degradation patterns. By, for example, monitoring humidity levels, the organisation can identify emerging faults before they lead to actual breakdowns. Such expanded data collection is important for strengthening the base level of the system pyramid and thereby also creating vertical information flows that can lead to strategic decision support.

6.2.1 Data Quality

In addition to data availability and system integration, data quality is important for the ability to develop predictive maintenance. Predictive maintenance depends on data that is consistent, comparable and sufficiently detailed to support analysis over time. The empirical finding shows that the current inspection data contains valuable information, but its analytical usefulness is limited by variation in assessments practices, broad response categories, incomplete reporting and reliance on free-text comments.

The checklist used during inspections provides a structure for data collection. This enables a basic standardisation of what is to be observed, but at the same time limits the information from the data. Assessments are captured in binary or broadly defined categories, which makes it difficult to analyse gradual changes over time. For example, a component might show minor corrosion during one inspection, and then more visible corrosion at the next, and eventually leakage or functional failure. If the reporting format does not capture these changes consistently, it becomes difficult to create a reliable degradation history. The limited level of detail means that minor variations in the condition of components risk being lost, even though such changes could be important for identifying early signs of degradation.

Furthermore, the empirical material shows that inspection assessments are dependent on individual judgement. Even when checklists are used, the interpretation of what constitutes, for example, a “moderate” or “serious” impact can vary between technicians. This variation contributes to inconsistent data quality and can make it difficult to compare different inspection occasions, objects and geographical areas. The lack of common assessment scales thus limits the possibility of using inspection data for more advanced analysis.

Attempts to standardise these assessments have reportedly been difficult. This indicates a challenge in translating tacit field knowledge into structured and repeatable assessment criteria. The organisation needs inspection data that is structured enough to support comparison, while still allowing technicians to capture the complexity of real inspection situations.

Another issue concerns incomplete reporting. The empirical material shows that historical information is available in the systems, but that it sometimes is incomplete. Not all measures are reported consistently, for example recurring or temporary interventions. This means that the component history may not fully reflect the actual load or the problems an asset has been subjected to over time. The need for recurring temporary actions may be early indicators of underlying degradation or repeated environmental exposure. If they are not documented consistently, the system history could underestimate the actual maintenance load and fail to capture signals that could indicate risk. The ability to identify long-term patterns and correlations between conditions, events and actions is reduced.

A comparison with Mälarenergi shows that their current IT systems allow for the systematic monitoring of repetitive tasks, such as frequent pumping in specific chambers. This shows that the limitations identified are also to how data is recorded and maintained over time.

This indicates that data quality could also be a work-process issue. The quality of the data could depend on how reporting fits into daily work. If documentation is perceived as time-consuming, unclear or disconnected from later decision-making, reporting may become uneven. Documentation contributes to better prioritisation and not only to administrative control. In this sense, improving data quality requires both better system design and organisational learning.

Overall, shortcomings in structure, level of detail and historical data mean that the data collected is largely suited to documentation and operational monitoring, rather than analysis over time. Although the data provides valuable descriptions of the condition of the assets at the time of inspections, it often lacks the detail and consistency required to build reliable time series. This limits the potential to use existing data as a basis for predictive models and proactive planning and contributes to maintenance work continuing to be dominated by reactive and descriptive approaches.

An improvement could be to develop clearer condition scales for recurring inspection categories. Instead of relying primarily on broad response options, the checklist could include more detailed levels for conditions. Another improvement could be to ensure that recurring temporary actions are recorded as part of the asset history. Repeated pumping, cleaning, temporary sealing and other minor interventions should be documented in a way that allows them to be analysed over time. Such actions may appear minor when viewed individually, but repeated occurrences can indicate chambers or components with higher degradation risk. In predictive maintenance, these repeated interventions can be seen as potential signals of future failure.

The uncertainty surrounding what constitutes relevant data is particularly evident at Mälarenergi, which takes a more cautious stance to predictive approaches. Mälarenergi points out that, even with the available data, it remains unclear which specific parameters indicate future risks, and that meaningful insights require a complex connection of different data sets, which is often lacking.

Similar challenges regarding relevant parameters are expressed by Öresundskraft. Despite their extensive sensor coverage, they emphasise that the system's usefulness ultimately depends on the quality of the entered data. They highlight a risk associated with the human factor, whereby technicians may provide incomplete information during manual reporting, which could hinder the detection of gradual changes and future trend analyses. By combining information from Vattenfall and the comparing organisations, the importance of high-quality data is illustrated. Another highlighted challenge by all organisations is the extracting and contextualising of meaningful data to enable predictive decision-making.

6.3 Decision-Making

The current maintenance process is closely connected to professional experience, practical constraints and manual interpretation of available information. Inspection data are used as input in the decision-making process, but they do not function as part of a formalised or systematic decision-support model. Instead, decisions concerning fault prioritisation and corrective actions are largely made through manual assessment, where technical severity is weighted against operational urgency, available budget, safety considerations and coordination with other planned activities.

A feature of the decision-making process is that it depends on the information generated through inspections. However, as discussed previously, inspection data is partly shaped by subjective assessments. The interpretation of different conditions may vary between technicians. This means that the information used in the decision-making process is not fully standardised. Consequently, later prioritisation decisions are influenced by how a condition has been interpreted and documented during inspection.

This creates a challenge for consistency. If similar faults are described differently or if the level of detail varies between inspection reports, it could become difficult to compare faults across chambers and over time. The fault list provides an overview of reported issues, but the prioritisation of these issues requires manual interpretation. The project manager reviews the fault list and determines which measures should be carried out first. This process is based on an overall assessment of urgency, risk, cost and feasibility.

Professional experience is necessary because maintenance decisions could involve contextual factors that are difficult to capture in standardised data fields. The empirical findings show that the seriousness of a fault depends on several factors such as its location, accessibility, surrounding infrastructure and public safety. This illustrates that maintenance prioritisation requires situational judgement. At the same time, the current dependence on individual judgement creates vulnerability in the decision-making process. Since prioritisation is largely based on the project manager's experience, and available overview, the reasoning behind decisions may not always be fully transparent or traceable. This can make it difficult to evaluate why certain faults were prioritised over others. It may also reduce organisational learning, since the logic behind previous decisions is not stored in a way that can be reviewed or reused in future prioritisation processes.

Furthermore, prioritisations are influenced by budgetary constraints. Thus, prioritisation is also determined by the practical and economic conditions under which maintenance work is carried out. The empirical findings also show that maintenance planning is linked to reinvestment planning. This reflects a strategy where assets are used for as long as they remain functional and meet safety requirements, rather than being replaced based on predicted failure.

Coordination with other organisational units and external parts is another aspect of the decision-making. Maintenance actions need to align with reinvestment planning and municipal development plans. This coordination is essential to avoid inefficient use of resources, and it also affects timing. The broader planning context explains why some faults are not addressed immediately, even when they are known. Sometimes, temporary measures can stabilise a fault until it can be included in a larger maintenance project. This approach may be beneficial from a resource-efficiency standpoint, but it requires that known risks are monitored and followed up systematically. If temporary solutions are not documented and linked to future planning, there is a risk that postponed faults become normalised or remain unsolved longer than intended. Thus, decision-making also relies on keeping reliable connections between temporary actions, risk status, and future intervention plans.

The current process can be described as experience-based and operationally flexible, but only partly systematic. Its strengths lie in the personnel's ability to adapt decisions to local conditions and available resources. However, its limitation is that decision criteria are not always explicit, comparable, or traceable. This creates a gap between the knowledge used in practice and the information available for organisational learning and predictive development. A more structured decision-support approach could help bridge this gap. Such an approach should not replace professional judgement but instead make it more explicit and easier to compare. For example, recurring decision factors like severity, occurrence, monitoring possibility, maintenance capability, cost level, accessibility, and coordination potential could be documented through standardised assessment criteria. This would allow the organisation to maintain the contextual flexibility of current decision-making while increasing transparency and consistency. It could also create a foundation for risk-based prioritisation and a gradual introduction of predictive maintenance methods.

6.4 Evaluation of Predictive Maintenance Methods Given Current Conditions

The suitability of different predictive maintenance methods should be evaluated in relation to the organisation's data maturity, inspection practices and decision-making processes. Several predictive approaches discussed in the literature may be theoretically relevant for DH networks, but their practical applicability depends on having the right data infrastructure, system integration and organisational routines in place.

Data-driven methods appear less suitable under the current conditions, which include limited data standardisation, fragmented data sources and subjective assessments during inspections. Methods such as machine learning or data mining requires large amounts of structured, consistent, and representative historical data to identify patterns and generate reliable predictions. However, available inspection data lacks the standardisation required to serve as training data. Without significant changes to data collection, these methods risk producing misleading results or creating a false sense of precision.

Probabilistic approaches, such as frequency-based models using historical information and Bayesian state estimation, can also be seen as potential alternatives for determining the probability of failure. These methods offer a more systematic basis for probability assessments. This is done either by estimating probabilities based on historical occurrences of failures, or by updating existing knowledge with new information, as done in Bayesian state estimation. In theory, this could reduce reliance on pure expert judgements within an FMEA framework and create a more systematic basis for assessing how often failures are expected to occur.

However, these approaches would currently face limitations in the maintenance organisation in Uppsala. The frequency-based model using historical information require access to consistent and complete historical data, where recurring events are recorded in a comparable manner over time. The fragmented data may cause observed frequencies to reflect how data is recorded rather than the actual occurrence of faults. Similarly, Bayesian state estimation requires a sufficiently stable and structured data set to be able to update probabilities. At present, due to the limited standardisation of inspection assessments, the observed data is too uncertain to enable reliable probability updates.

This means that the frequency model risk providing a distorted picture of reality due to inconsistent reporting, whilst Bayesian state estimation risk being influenced by initial assumptions rather than by empirical data. Despite their theoretical advantages, their usefulness is limited by the lack of consistency and comparability in the data. This contrast with model-based methods, which are based on an explicit description of how errors evolve over time.

Model-based methods may provide an alternative to more data-dependent approaches, as they can rely to a greater extent on technical understanding and established expert knowledge of the system's behaviour. Model-based methods could, in theory, coexist more effectively with the working methods already in use. The conditions required for model-based methods are only partially met. Inspection assessments are characterised by subjective interpretation and limited standardisation, and the history of conditions and actions is fragmented. Even though model-based methods are more tolerant of limited data sets than, for example, machine learning, they are still sensitive to inconsistent reporting and a lack of traceability at component level. In practice, a model-based approach would therefore not replace existing experience-based processes but rather serve as a structuring framework that clarifies the relationships between condition, degradation and risk.

The comparison with other actors also indicates that the challenges in implementing predictive maintenance are not limited to Vattenfall but rather reflect broader issues within the DH sector. Although the companies in the comparison have achieved a higher degree of system integration, they still have ongoing challenges in combining data from different sources and in reliably identifying which specific parameters best indicate future risks. This also indicates that predictive maintenance in DH is still under development, and that access to data does not automatically mean that it is suitable for prediction.

The experiences of these more digitally mature organisations show that transforming data into forward-looking insights is not straightforward. This underscores that the move towards advanced models requires extensive standardisation of both data quality and component history. Placing Vattenfall's situation within this wider context strengthens the argument that the gradual transition towards a predictive approach is part of a larger structural development.

6.5 Fault Prioritisation and Potential of FMEA Based Frameworks

In contrast to the current prioritisation of faults, which is primarily based on the project manager's personal knowledge and experience, FMEA offers a more standardised approach to handling the same type of assessments. The method is based on the systematic analysis of identified faults according to defined dimensions. In practice, this means that the considerations already made within the framework of current manual prioritisation are broken down and made explicit through common scales and criteria. Therefore, the same factors can be considered, with the difference in how these factors are structured and documented.

The reason why a modified FMEA can contribute to predictive maintenance is that the method focuses on identifying and prioritising potential faults before they lead to more serious consequences. The modified FMEA approach serves as a support for predictive maintenance planning and can thus help to detect developing issues and take preventive action before a failure occurs. FMEA can therefore be seen as a knowledge-driven method that supports a more predictive approach.

FMEA can be regarded as a practically feasible method under current conditions. The method is based on structured assessments of the Occurrence, Severity, and the possibility of Monitoring and Maintenance. This means that the method can be applied within the framework of current working practices, where decision-making is largely based on experience and qualitative assessments.

This shows that the transition from manual prioritisation to an FMEA framework involves structuring of the knowledge and decisions already used in practice. Whilst manual prioritisation allows considerable scope for adapting to specific situations, FMEA enables the creation of a support tool and provides traceability as to why certain faults are prioritised over others. This creates the conditions for increased transparency and comparability over time, whilst professional judgement continues to form a central part of decision-making.

Overall, the choice of predictive maintenance method needs to be adapted to the organisation's actual circumstances rather than to the methods' theoretical potential. FMEA can be seen as a realistic first step towards more structured and forward-looking maintenance, as it builds on existing knowledge and decision-making processes. More advanced methods appear to be long-term possibilities that require improved data quality, increased system integration and a higher degree of standardisation before they can be applied.

6.5.1 Occurrence

Within the Occurrence dimension, Markov-based degradation models, and in particular Degradation Hidden Markov Models, emerge as a possible alternative for supporting probability assessments within an FMEA-based framework. DHMM can be viewed as a potential aid to improving the assessment of Occurrence within an FMEA-based framework. A challenge in FMEA is determining how likely a particular failure is to occur, something that typically rely on structured assessments but is currently not systematically applied in the organisation. Markov-based models theoretically offer a means of estimating such probabilities by modelling how components gradually transition between different states over time, whilst also allowing for uncertainty in observations.

However, the conditions for applying DHMM is currently not met within the organisation. The model requires consistently linked state data, a clear component history and relatively stable observations over time. Currently the lack of sufficient data makes it difficult to calibrate and use such a model. Despite these limitations, DHMM can be seen as relevant in a long-term perspective. If data quality, traceability and history are improved, for example through more structured recording of conditions and actions, DHMM could potentially be used to complement FMEA by providing a more systematic basis for probability assessments.

6.5.2 Monitoring and Maintenance

The expanded FMEA dimension of Monitoring & Maintenance can be seen as particularly relevant in relation to the work processes identified in the organisation. To achieve predictive fault handling there is a need to know when faults happen. To do this it is necessary to know how the system can and should be monitored. Many of the faults identified during inspections are managed through continued monitoring, temporary measures or planned action at a later date.

The severity of a fault is also determined by how well it can be monitored and managed in practise. Unlike the traditional detectability dimension in FMEA, which focuses on the probability that a fault will not be detected before it leads to consequences, the Monitoring & Maintenance dimension captures the organisation's actual scope for action. Empirical findings shows that technicians and project managers today make ongoing assessments of whether a fault can be kept under control through temporary measures. These types of considerations are central to current prioritisation but take place implicitly. By including Monitoring & Maintenance as an explicit dimension in the FMEA structure, these assessments can be made explicit and compared across different faults and assets. The dimension thus enables a more operationally focused prioritisation where technical conditions are weighed against operational capabilities. For example, a fault with a high probability and potentially serious consequences may be given a lower priority if there are good opportunities for monitoring and management, whilst a fault that is difficult to monitor and has limited scope for preventive measures may be given higher priority despite a lower frequency. In this way, the Monitoring & Maintenance dimension reflects how maintenance decisions are already made in practice, whilst also providing a framework for structuring these considerations.

In relation to predictive maintenance, Monitoring & Maintenance also helps to link reactive and more forward-looking approaches. By systematically assessing monitoring and maintenance options, the conditions are created to gradually shift the focus from emergency interventions towards the planned management of known risks. The dimension can thus be seen as a central component of an FMEA-based framework that is adapted to the data maturity and work processes identified in the organisation, whilst supporting a gradual shift towards more structured and predictive prioritisation decisions.

Since the Monitoring & Maintenance scale concerns the ability to monitor and manage faults, it needs to be refined based on how maintenance is carried out in practice. The empirical material shows that many faults in chambers are managed through follow-up, recurring interventions and planned measures over time. This means that the Monitoring & Maintenance scale can be made more detailed than simply focusing on whether the fault can be detected or not, and that it should reflect the degree of control they have over the potential fault. The scales in Table 1 and Table 2, can be seen as somewhat general but provide a good basis for developing and structuring a scale specific to Vattenfall's DH network in Uppsala. Each level on the scale should reflect the degree of practical control, for example, the extent to which a fault can be addressed through recurring interventions, managed through temporary solutions, or whether it requires immediate action.

The empirical material shows that there is potential for monitoring in certain chambers for specific types of faults, for example regarding water in chambers equipped with level alarms. In these cases, it can be said that the monitoring potential is high and should be assigned a high score. In contrast, in chambers lacking alarm systems, the monitoring potential is lower for faults. For example, in the case of corrosion or structural degradation that is only detected during inspections, the monitoring potential is lower because the ability to track the fault's development over time is limited and highly dependent on manual checks. This means that monitoring potential differs between different types of faults and between different chambers depending on the type of monitoring system installed. Therefore, Monitoring & Maintenance assessments must consider both technical conditions, such as access to alarms or sensors, and operational factors, such as how frequently inspections are carried out and how easy it is to follow up on a known problem.

Furthermore, a fault lacking continuous monitoring may in some cases still have a relatively high monitoring potential if it is easy to follow up through recurring interventions. Similarly, a fault with technical monitoring may still have limited monitoring potential if follow-up is difficult to carry out in practice. Thus, the Monitoring & Maintenance scale is a combination of access to data and the organisation's actual ability to act on this information.

6.5.3 Severity

When it comes to the Severity scale, it is important that the scale is linked to concrete effects within the system. The empirical material suggests that severity should be assessed based on technical impact, but also in relation to factors that affect operations, security and the need for emergency response. This means that each level on the scale should be defined based on clear and relevant descriptions, for example linked to operational disruptions, the risk of leakages, the impact on the surrounding area or the need for immediate action.

Each level on the scale should therefore be defined using concrete descriptions. These can be linked to operational disruptions, the risk of leakages, the impact on the surrounding area or the need for immediate action. In this way, the scale can be linked to actual work rather than general definitions. By linking the values to specific situations, the scope for individual interpretation is reduced, which contributes to more consistent assessments between faults and over time.

Within an FMEA-based framework, the Severity assessment should be informed by historical experience of how similar faults have affected the system. In chambers where faults have historically led to serious consequences, similar faults should be assessed as more critical. Contrary, in cases where similar types of faults have historically been managed without major consequences, the severity assessment should be lower. Thus, Severity is shaped by what has occurred in the past and how the system has been affected in practice.

This means that severity assessments risk becoming dependent on local experience and individual perceptions if they are not structured. If incidents are not documented consistently or if experiences are not shared systematically, the same type of fault may be assessed differently depending on who is making the assessment or in which part of the network it occurs. To create a more consistent Severity scale, real-world incidents and their consequences should be linked to criteria, where different levels are related to typical outcomes such as operational impact, security risk or the need for emergency measures.

As discussed earlier, severity assessments are context-dependent and influenced by factors such as location, accessibility and surrounding infrastructure. This implies that similar faults may require different Severity levels depending on where they occur in the DH network. Severity assessments therefore need to reflect the external factors that influence how serious the situation becomes in practice. In relation to the design of the FMEA scale, this implies that a certain degree of flexibility is required, where the levels of the scale must be interpretable in relation to local conditions, whilst still being sufficiently defined to allow for comparability.

6.5.4 Limitations

There are also limitations to an FMEA-based approach that need to be taken into account when implementing. A challenge will be the risk of false precision, where the use of numerical scales can give an impression of objectivity and accuracy, even though the assessments are based on qualitative and subjective judgements. When such assessments are translated into numerical values, there is a risk that the variation is concealed behind seemingly precise figures, which may influence how the results are interpreted in the prioritisation process.

A limitation is the method's dependence on how the scales are defined and applied in practice. Since FMEA is based on Occurrence, Severity and the Monitoring & Maintenance dimension being assessed according to criteria, the outcome is directly dependent on how clear and operationally relevant these criteria are. If the scales are vaguely defined, or if different actors interpret them in different ways, the comparability between assessments is affected, and so will the method's reliability. This also implies a need for continuous calibration, where scales and assessments need to be adjusted based on experience from actual outcomes.

6.6 Organisational and Strategic Implications

A strategic issue could be whether the implementation of predictive maintenance within Vattenfall's DH network in Uppsala is practically and economically justified given the current organisational and technical conditions. For an aging DH network, one of the primary potential benefits lies in the ability to defer resource-intensive reinvestments by prioritising and planning maintenance measures more efficiently.

At the same time, the implementation of predictive maintenance also presents organisational and technical challenges and requires financial and resource investments. Enabling a more predictive approach requires technical investment in sensors, system integration and data infrastructure, but also long-term organisational efforts linked to standardisation, documentation and changes to work processes. In practice, this means that a gradual transition to predictive maintenance is likely to be more realistic than the immediate implementation of advanced data-driven models. An important aspect of this development is the level of detail in data collection and documentation. While more detailed and structured data can improve the possibilities for analysis and predictive maintenance, it might also require additional time during inspections and other related activities. This creates a balance to be considered between the value generated by the increased data quality and the resources required to collect it.

Vattenfall could face a financial trade-off regarding the implementation of predictive maintenance. Research indicates that implementation could yield financial gains, whilst maintenance costs are expected to fall. Considering this, for an ageing network such as Uppsala's, there could be potential for savings if reinvestments can be postponed by optimising the service life of existing components.

The compared organisations demonstrate two different approaches to the dilemma. Mälarenergi is somewhat more cautious regarding investment in predictive maintenance and raises questions about the balance between cost and benefit. That is to say, whether the actual value of being able to predict faults outweighs the investment costs currently associated with technology and system integration. The organisation instead places emphasis on continuous, minor maintenance work. Öresundskraft has a different view of the matter, as they have a positive attitude towards predictive approaches. The organisation has invested in new technologies and decision-making systems to analyse more parameters, expecting it to result in a more predictive way of working. One reason for this positive attitude may be that previous investments in predictive maintenance have proved profitable.

For Vattenfall, it may currently be premature to make large-scale investment decisions regarding predictive maintenance, as such implementation could require significant financial resources and organisational changes. A more appropriate first step could instead be to conduct an internal evaluation of the potential benefits that predictive maintenance might provide in contrast to the expected costs for implementation. Such an evaluation could then include a comparison between more advanced predictive maintenance and simpler structured methods like FMEA. This could help the organisation to find which level of predictive maintenance is most feasible and beneficial in the long term given current conditions and priorities.

6.7 Future Studies

The findings of this study point to several areas where future research could strengthen the basis for predictive maintenance in DH networks. The proposed FMEA-based framework should be tested in practice. In this thesis, FMEA is discussed as a suitable first step towards more structured and predictive maintenance, as it can build on the knowledge and assessments already used in the organisation. However, its practical value cannot be fully evaluated without application in an operational setting. Future studies could apply the framework to a selected group of chambers and compare the outcome with the current decision-making practices. This would make it possible to evaluate whether the framework improves transparency, consistency and traceability in maintenance prioritisation.

Further research should also examine how different types of condition indicators can be used to understand degradation in chambers over time. Current predictive maintenance research often relies on continuous measurements or historical failure data, while chamber inspections may include visual assessments, alarm data, temporary interventions and local environment conditions. More knowledge is needed about which indicators are most meaningful for predicting future maintenance needs. The purpose would not only be to collect more data, but to understand which data reflect degradation and future risk.

Finally, future research should evaluate the value and limitations of predictive maintenance in ageing DH infrastructure. Implementing improved data collection, sensor systems and system integration requires time and resources. More studies are needed to assess when such investments are justified. This is especially relevant for infrastructure where assets have long lifetimes and maintenance decisions must balance risk, cost and long-term reinvestment planning. Such research could help clarify when predictive maintenance provides enough value to justify the investment, and when simpler, structured methods may be more appropriate.

7. Conclusions

This thesis has examined the conditions for developing inspection and maintenance practices related to DH chambers towards a more predictive maintenance approach. In the case of Vattenfall’s DH network in Uppsala, there are structured inspection procedures in place for chambers. Inspections are conducted according to fixed intervals based on classification of chambers, with more critical chambers being inspected more frequently. Digital systems are used in the inspection process to systematically document the condition of components, as well as inspection and maintenance activities.

Furthermore, limitations in system integration, data quality, and fragmented and incomplete historical data limit the transition towards predictive maintenance. Shortcomings in system integration reduce the ability to link sensor data, inspection data and planning decisions, which hinders analysis over time. Data quality is influenced by subjective assessments and simplified categorisations, which makes it difficult to compare and analyse the data. The fragmented data makes it difficult to identify long-term degradation processes, thereby complicating the process of predicting when a component will need maintenance or be replaced.

FMEA can be considered a suitable method for Vattenfall to initiate a transition towards more predictive maintenance given the current conditions. Rather than replacing current work processes, FMEA provides a better framework for structuring and formalising the knowledge currently applied in the prioritisation of maintenance. By implementing the method, transparency, traceability and comparability in decision-making could increase, supporting a more systematic and predictive approach. Furthermore, by including the Monitoring & Maintenance dimension, prioritisation can be adapted to the organisation's ability to control faults during ongoing operations. The potential for more advanced methods is limited given current data conditions. Although a model such as DHMM could contribute to more objective assessments of Occurrence within an FMEA framework, such an application would require higher quality data.

What is required to enable predictive maintenance and implement a FMEA-framework within the DH network is developing a more detailed condition scale and uniform criteria. By doing this, Vattenfall can reduce the scope for individual interpretations and generate more suitable data. In addition, by improving how data is recorded and maintained over time, historical information can be transformed from administrative notes into reliable time series that enable the identification of long-term patterns.

Strengthening the connection between inspection data and planning would allow for fault reporting to be more directly linked to work order generation, reducing dependency on individual judgement and improving the continuity and traceability of data. To enable predictive work, information needs to flow across system levels, from alarms and inspection tools to decision-making and planning processes. Without this integration, digitalisation remains fragmented and the analytical potential is not fully realised. Another step towards enabling predictive maintenance is to increase the amount of data generated in the chambers, thereby making it easier to identify patterns between different conditions and degradation. These developments could also create the organisational conditions required to support the implementation of an FMEA-based predictive maintenance framework.

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Appendix A

This appendix presents the interview guides used to collect the empirical material for the study. Since the interviews were conducted in Swedish, the original interview questions are presented in Swedish. To improve accessibility and transparency, an English translation of each topic and question is provided directly after or below the original formulation. The appendix is divided into sections A1-A7, where each section contains the interview guide used for the corresponding interview.

The guides were developed based on the theoretical framework and refined iteratively as the research progressed. Each guide was adopted to the specific role and competence of the respondents, while maintaining a consistent thematic structure related to inspection practices within the DH network. The interview guides served as a flexible support during the interviews and were adjusted when necessary to allow for follow-up questions and deeper exploration of relevant topics.

Appendix A1 – Interview 1

Organisation och roller / *Organisation and Roles*

- Kan ni beskriva era roller och ansvar kopplat till fjärrvärmenätets underhåll?
  Could you describe your roles and responsibilities in relation to the maintenance of the district heating network?
- Finns det någon samverkan med andra enheter?
  Is there any collaboration with other units?
- Vilka roller är involverade i beslut om åtgärder och prioriteringar?
  Which roles are involved in decisions concerning measures and prioritisation?

Övergripande mål och strategier / *Overall Goals and Strategies*

- Vilka är de övergripande målen för underhållsarbetet?
  What are the overall goals of the maintenance work?
- Hur balanseras kortsiktiga åtgärder mot långsiktig livslängd och underhållskuld?
  How are short term measures balanced against long-term service life and maintenance backlog?

Fysiska inspektioner / *Physical Inspections*

- Hur planeras ronderingsarbetet?
  How is the inspection work planned?
- Vilka faktorer styr när och var ni ska rondera?
  Which factors determine when and where you conduct inspections?
- Prioriteras särskilda kammare?
  Are particular chambers prioritised?
- Hur ser inspektionsarbetet ut på en övergripande nivå?
  What does the inspection work look like at an overall level?

Digitala system i stort / *Digital Systems in General*

- Vilka huvudsakliga system används idag för dokumentation, uppföljning och planering?
  Which main systems are currently used for documentation, follow-up and planning?
- Hur upplevs stödet från dessa system i beslutsfattande?
  How is the support provided by these systems perceived in decision-making?

Appendix A2 – Interview 2

Genomförande / *Inspection Procedure*

- Hur många personer hos er arbetar regelbundet med ronderingar?
  How many people in your organisation regularly work with inspections?
- Hur fördelas arbetsuppgifterna mellan er?
  How are the tasks distributed among you?
- Hur går en rondering praktiskt till, steg för steg?
  How is an inspection carried out in practice, step by step?
- Vad kontrolleras i en kammare?
  What is inspected in a chamber?
- Vilka verktyg används under inspektionen?
  Which tools are used during the inspection?
- Hur lång tid tar en typisk rondering?
  How long does a typical inspection take?

Bedömning / *Assessment*

- Hur bedöms exempelvis rost, sprickor och skador på konstruktioner?
  How are, for example, corrosion, cracks, and structural damage assessed?
- Vilka verktyg används som stöd för bedömning?
  Which tools are used to support the assessment?
- I vilken utsträckning påverkar erfarenhet och individen bedömningen?
  To what extent do experience and the individual affect the assessment?
- Hur har ni blivit upplärda att bedöma och rapportera?
  How have you been trained to assess and report?
- Finns det punkter som ni tycker saknas på checklistan?
  Are there any elements that you think are missing from the checklist?

Efterarbete / *Follow-up Work*

- Hur dokumenteras resultaten av ronderingen?
  How are the results from the inspection documented?
- I vilka system förs informationen in?
  In which systems are the information entered?
- Hur används informationen efter att den rapporterats?
  How is the information used after it has been reported?
- Hur ofta tittar ni tillbaka på historiken i rapporterna och i vilka situationer?
  How often do you refer to the history in the reports, and in which situations?

Avslutande reflektioner / *Concluding Reflections*

- Finns det något ni vill tillägga om inspektioner, datainsamling eller arbetsprocessen som vi inte har pratat om?
  Is there anything you would like to add regarding inspections, data collection or the work process that we have not discussed?
- Är det något vi har missat att fråga om som är viktigt för att förstå ert arbete?
  Is there anything we have omitted to ask about that is important for understanding your work?

Appendix A3 – Interview 3

Larm och upptäckt / *Alarms and Detection*

- Kan ni ge exempel på ett kritiskt fel?
  Could you provide an example of a critical fault?
- Vilka typer av larm förekommer idag?
  What types of alarms are currently used?
- Hur når larm fram till beredskap?
  How are alarms communicated to the technician on call?
- Vad klassas som ett kritiskt larm?
  What is classified as a critical alarm?
- Vad klassas som en kritisk situation?
  What is classified as a critical situation?
- Hur hanteras de kammare som inte har larm?
  How are chambers that do not have alarms managed?

Tillförlitlighet / *Reliability*

- Hur vanligt är falsklarm?
  How common are false alarms?
- Förekommer uteblivna larm?
  Do missed alarms occur?
- Hur upplevs tilliten till larm- och sensorsystem?
  How is the trust in the alarm and sensor systems perceived?

Bedömningar / *Assessments*

- Kan ni ge exempel på situationer där olika tekniker gör olika bedömningar?
  Could you provide examples of situations in which different technicians make different assessments?
- Hur skulle en bättre standardisering se ut enligt er?
  What would better standardisation look like?
- För vilka delar av kammaren är oenigheterna störst?
  For which parts of the chamber are disagreements greatest?

Prioritering av åtgärder / *Prioritisation of Measures*

- Hur prioriterar ni fel idag?
  How do you currently prioritise faults?
- Vilken typ av kostnader är störst när det kommer till fel?
  Which types of costs are greatest when it comes to faults?
- Hur skulle ni vilja prioritera om ni hade mer flexibilitet?
  How would you like to prioritise if you had greater flexibility?

- Vilka typer av fel är svårast att prioritera och varför?
  Which types of faults are the most difficult to prioritise, and why?
- Hur ofta får ni omprioritera på grund av yttre faktorer?
  How often do you have to reprioritise due to external factors?
- Hur ses det på balansen mellan förebyggande arbete och akuta åtgärder?
  How is the balance between preventive work and emergency measures viewed?
- Hur väl fungerar dagens budgetprocess för att hantera både mindre och större åtgärder?
  How well does the current budgeting process function for managing both minor and major measures?

Appendix A4 – Interview 4

Systemöversikt / *System Overview*

- Hur används UTG, Trimble NIS och andra system i det dagliga arbetet?
  How are UT, Trimble NIS and other systems used in day-to-day work?
- Hur hänger systemen ihop från inspektion till åtgärd?
  How are the systems connected from inspection through remedial actions?

Dataanvändning / *Data Use*

- Hur används historik från tidigare ronderingar?
  How is historical information from previous inspections used?
- Ger data i dagsläget någon nulägesanalys eller beslutsstöd?
  Does the data currently provide any situational analysis or decision support?
- Vad används insamlade data mest till i praktiken?
  What are the collected data primarily used for in practice?

Förbättringspotential / *Potential for Improvement*

- Upplever ni brister i datakvalitet eller datatäckning?
  Do you perceive any shortcomings in data quality or data coverage?
- Vilken data skulle ni vilja ha bättre tillgång till?
  What data would you like to have better access to?
- Finns det funktioner eller verktyg ni saknar idag?
  Are there any functions or tools that you currently lack?
- Hur ser ni på möjligheten att arbeta mer prediktivt?
  How do you view the possibility of working more predictively?
- Finns det feltyper där ni idag kan se mönster (exempelvis årstid, plats, tidigare historik, konstruktion)?
  Are there types of faults for which you can identify patterns today, such as season, location, previous history, or construction type?

Appendix A5 – Interview 5

Reinvesteringsstrategi / *Reinvestment Strategy*

- Hur definierar ni när en ledning ska bytas ut?
  How do you define when a pipeline should be replaced?
- Vilka faktorer är viktigast? Ålder, material, läckhistorik, kostnad?
  Which factors are most important? Age, material, leakage history, cost?
- Hur används skadestatistiken i besluten?
  How are damage statistics used in the decisions?

Prioritering / *Prioritisation*

- Hur är processen från identifierat problem till projekt?
  What is the process from an identified fault to a project?
- Hur lång framförhållning har ni i planeringen?
  How far ahead do you plan?
- Hur hanteras akuta behov kontra långsiktig strategi?
  How are urgent needs handled in relation to long-term strategy?

Beslutsstöd och verktyg / *Decision Support and Tools*

- Hur används verktyg och modeller?
  How are tools and models used?
- Vad ser ni som styrkor och begränsningar i modellen?
  What do you see as the strengths and limitations of the model?
- Hur kombineras resultat från modellerna med erfarenhet och dialog?
  How are results from the models combined with experience and dialogue?

Data och utveckling / *Data and Future Development*

- Hur bedömer ni kvaliteten på indata idag?
  How do you assess the quality of the input data today?
- Vad krävs för att möjliggöra mer prediktivt underhåll?
  What is required to enable more predictive maintenance?
- Vilken roll spelar digitalisering framåt?
  What role will digitalisation play going forward?

Appendix A6 – Interview 6

Bakgrund och kontext / *Background and Context*

- Kan du kort beskriva din roll och erfarenhet inom fjärrvärme?
  Could you briefly describe your role and experience within district heating?
- Kan du beskriva det projekt du var involverad i och dess huvudsakliga syfte?
  Could you describe the project you were involved in and its main purpose?
- Hur var det tänkt att resultaten skulle presenteras?
  How were the results intended to be presented?

Data och begränsningar / *Data and Limitations*

- Vilka typer av data användes i projektet?
  What types of data were used in the project?
- Saknades det någon viktig typ av data?
  Was any important type of data missing?
- Fanns det begränsningar kopplade till datatillgång eller datadelning?
  Were there any limitations related to data access or data sharing?

Implementering och utmaningar / *Implementation and Challenges*

- Vilka svårigheter uppstod i att använda resultaten i praktiken?
  What difficulties arose in using the results in practice?
- På vilken nivå var det möjligt att göra användbara prediktioner?
  At what level was it possible to generate useful predictions?
- Uppstod det organisatoriska hinder?
  Did any organisational barriers arise?
- Vilka faktorer gjorde att ni inte kunde gå vidare med projektet?
  Which factors prevented the project from progressing further?

Lärdomar och framtida utveckling / *Lessons Learned and Future Development*

- Vilka är de viktigaste lärdomarna från projektet?
  What are the most important lessons learned from the project?
- Utifrån din erfarenhet, vad krävs för att ett fjärrvärmebolag ska kunna arbeta mer prediktivt?
  Based on your experience, what is required for a district heating company to adopt a more predictive way of working?

Appendix A7 – Interview 7 and Interview 8

- Hur är arbetet med inspektion och underhåll av kammare organiserat?
  How is the work related to inspection and maintenance of chambers organised?
- Hur planeras inspektionsarbetet?
  How is inspection work planned?
- Vilka likheter och skillnader identifierar ni mellan ert arbetssätt och Vattenfalls arbetssätt?
  What similarities and differences do you identify between your approach and Vattenfall's approach?
- Vilka digitala system eller verktyg används för att dokumentera inspektioner, identifierade fel och genomförda åtgärder?
  Which digital systems or tools are used to document inspections, identified faults and completed corrective actions?
- I vilken utsträckning används historiska data som underlag för planering och prioritering av underhållsinsatser?
  To what extent is historical data used as a basis for planning and prioritising maintenance activities?
- Vilka kriterier ligger till grund för prioritering av fel och åtgärder?
  Which criteria form the basis for prioritising faults and maintenance measures?
- Förekommer det idag någon form av prediktivt eller datadrivet underhåll inom organisationen?
  Is any form of predictive or data-driven maintenance currently applied within the organisation?
- Vilka hinder upplever ni för en ökad användning av prediktivt underhåll?
  What barriers do you perceive to the increased use of predictive maintenance?
- Vilka förutsättningar bedömer ni vara centrala för att möjliggöra en övergång mot ett mer prediktivt underhållsarbete?
  Which conditions do you consider central to enabling a transition towards a more predictive maintenance approach?