Public summary

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A JOURNEY TO PREDICTIVE MAINTENANCE IN THE FIRE PROTECTION INDUSTRY

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A journey to predictive maintenance in the fire protection industry

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1. Problem objective and goal

In the last few years, Company X introduced an innovation. This innovation exists of multiple sensors that can monitor several variables of a fire protection system. The sensors capture a lot of data which is stored. However, this data is currently not analyzed, and it is not known how to use this data to drive operational decisions. Additionally, Company X does not know if the current control system and sensors gather enough data to predict failures or if more sensors are needed. Creating and applying a predictive model in order to prevent malfunctions would ultimately result in better scheduling of the workforce. Furthermore, it would decrease costs involved in mechanical failures.

Research questions:

The main research question in this research is:

How can Company X create a predictive maintenance model in fire protection systems to decrease maintenance costs?

Phase 1: Current situation

In the first phase, an analysis of the current situation is done. This includes the current maintenance strategy, the error procedures and the available sensor data. The following three sub-research questions are answered to get a better understanding of these topics.

- **What maintenance strategy is currently used to prevent failures?**
- **What is the general procedure when a failure occurs in a system?**
- **Which variables are currently being monitored using sensors in the fire sprinkler systems?**

Phase 2: Literature Review

The second phase is focused on the literature that is available and applicable for Company X. Multiple aspects are taken into account. First, the maintenance techniques and the requirements for a failure prediction model are researched. Then, existing models for predicting failures based on sensor data and expert knowledge are investigated. Lastly, the most important and common failures in fire sprinkler systems are identified from existing research. This results in the following sub-research questions:

- **What maintenance techniques exist, and which ones relate to predictive maintenance?**
- **What are the requirements for a failure prediction model?**
- **What existing methods are available for predicting failures based on sensor data and expert knowledge?**
- **What are the most common failures in fire sprinkler systems identified in existing research?**

Phase 3: Failure analysis of Fire Sprinkler Systems

The third phase analyzes the failures that occur in fire sprinkler systems based on expert knowledge. Service mechanics and engineers are being interviewed to identify frequent failures. Then, the identified failures are cross-validated with the failures found in the literature. Finally, the key failures are selected and a relational data model is built to establish the relationship between the failures and the sensor data. The following research question is answered in this phase:

- **What are the most common and important failures in fire sprinkler systems and what variables are correlated to each failure?**

Phase 4: Solution design

In the fourth phase a solution design is created. This phase includes creating and comparing two failure prediction models to detect anomalies in the sensor data. Furthermore, an updating model is constructed so the selected failure prediction model can be updated when new data becomes available. Additionally, a framework is proposed to document new incoming failures and the most significant failures are analyzed to determine if more data is needed to predict these failures effectively. Hence, recommendations are given to Company X about gathering additional data. This results in three sub-research questions:

- **How can the identified models be created to predict failures?**
- **How can the selected model be updated in the future?**
- **How should incoming data be documented and what additional data should be gathered?**

Phase 5: Solution analysis

Phase five evaluates and analyzes the solution. It is reviewed how the solution adds value, and how it impacts the maintenance costs per year. This results in the following sub-research question:

- **How does the created prediction model impact the maintenance costs per year?**

Phase 6: Conclusion

The last phase analyzes all the answers to the sub-research questions and states the final conclusions. Recommendations about future developments and research are given to Company X, as well as the limitations of the current research.

2. Literature review

2.1 Maintenance techniques

Predictive maintenance has many definitions, and a lot of constructs are related to this topic. We want to find maintenance technique(s) that relate to predictive maintenance.

Predictive maintenance

Predictive maintenance employs specialized techniques to analyze equipment states during operation. Then it will predict when equipment will fail [1]. Predictive maintenance (or cognitive maintenance) not only optimizes equipment uptime and performance, but also reduces the time and labor costs of checking preventive maintenance [2]. Predictive maintenance has the aim of maximizing the useful life of the equipment and components while avoiding unplanned downtime and minimizing planned downtime [2].

Corrective maintenance

Corrective maintenance is carried out after a fault has been recognized [3]. Thus, only after a components breaks down the maintenance procedure is set in motion. Corrective maintenance is also known as run-to failure or reactive maintenance, and it leads to high levels of machine downtime and maintenance costs due to sudden failure [4].

Time-based maintenance

Time-based maintenance is a maintenance strategy based on fixed intervals, where maintenance actions are regularly taken based on predefined schedules. The decisions for maintenance are solely triggered by time, with preventive repairs [1]. It is also known as periodic-based maintenance. The intervals are determined based on failure time analysis; this can be failure time data as well as used-based data [4].

Condition-based maintenance

Condition-based maintenance is a type of maintenance that recommends actions based on the information collected through monitoring the parameters of the production system. It is a policy that tries to avoid unnecessary maintenance by only taking actions when there is evidence of abnormal behavior of a physical asset [5]. Predictive maintenance has a big role in the introduction to condition-based maintenance. There are multiple data-driven methods that have been proposed for predictive maintenance. Most of these methods implement condition-based maintenance solutions [6].

2.2 Requirements for a failure prediction model

One of the main limitations in predictive maintenance is the availability of data. Often, there is a gap between ambition and initially available data [7]. Tiddens et al. [8] define four types of data that are essential to separate: historical data, usage monitoring, load monitoring and health/condition monitoring.

1. Historical data

The main inputs for historical data are: technical knowledge, inspections and historical records of failures/costs. There is a difference between low-quality and high-quality historical data. Low-quality historical data only contain the basic and essential parameters such as the time to failure of a system [8]. High-quality historical data however, also includes information on historical usage, loads (including environmental stressors) or condition/health per group of systems (fraction of fleet, i.e., a specific unit or type) [8]. Historical data is gathered through manual registration methods, such as logbooks or databases, instead of detailed monitoring [8].

2. Usage monitoring

Usage monitoring data is mostly gathered out of operational data. This means measurements of operating hours, mileage, tons produced and/or process control data [8].

3. Load monitoring

Load monitoring data includes measurements of temperature, vibration, humidity, strain or electrical current.

4. Health or condition monitoring

Health or condition monitoring data is made up of signs of degradation or imminent failure. For example, vibrations, acoustics, temperatures, wear depths or data extracted from the measured response to identify the presence and magnitude of damage in the system [8].

It may look like Usage monitoring, Load monitoring and Health or condition monitoring are a part of high-quality historical data, but they are not. The main difference is that the variables in usage, load and health/condition monitoring are actually being measured with sensors (real-time monitoring). Historical data is not concerned about the real-time monitoring. Therefore, these are classified as different data types.

Getting insight into real-time deterioration of the individual asset and extrapolation to the future under constant conditions, requires a combination of these data types. At least high-quality historical data, health/condition monitoring and usage monitoring or load monitoring data should be available to achieve this [8].

2.3 Methods to predict failures

We will review several ways to predict failures. First, we will look at experience-based maintenance techniques. Then, methods for setting thresholds to detect anomalies are reviewed.

2.3.1 Experience based maintenance techniques

Multiple methods for predicting failures from sensor data and/or expert knowledge exist. Failure Mode and Effects Analysis (FMEA) is one of the methods which can be used for creating a predictive model. In this section, the different usages of this method are discovered.

Failure Mode and Effects Analysis (FMEA) allows for the processing of individual analysis of a system's sub-component. The analysis displays the various components with their respective failures and causes to gain better insight into the reliability of the system [9]. The FMEA method has been used in various research papers. For example, to study the reliability of wind turbine power generation systems or to get better insight in the reliability of machines or systems [10].

FMEA has four standard columns that are used to analyze machines or systems: Component/Unit, Failure Mode, Failure Cause, Failure Effect. Srivastava et al. [11] introduce a modified FMEA approach (FMEORA) in order to develop a predictive maintenance model. Two columns are added, defining the Average Output and the Output Range. For every failure, it is estimated what the resulting output of a sensor would be. When the machine breaks down, the specific failure model is identified with use of these ranges. However, these ranges do not really predict a breakdown, but help in identifying the failure when it occurred. Furthermore, only one output measure is selected in which multiple failures are identified. When creating an FMEORA, it is essential to have data on the outputs of each failure mode. Therefore, a standard FMEA approach is more practical when less data is available.

After identifying the failures, the Severity (S), Occurrence (O) and Detection (D) are rated from 1-10 correlating to the failure. These factors are rated with a 1 for indicating the least severe, most uncertain occurrence, and almost certain chance of detection of failure, respectively [12]. Then, the Risk Priority Number (RPN) is calculated. The RPN is a relative quantity indicating the risk associated with different failure modes of the components of machinery [12]. The general RPN (1) is calculated in the following way:

$$RPN = S \times O \times D \tag{1}$$

To calculate the RPN of a component (2) or the RPN of a subsystem (3) the following equations are used:

$$RPN_{component} = RPN_{Failure\ Mode\ 1} + RPN_{Failure\ Mode\ 2} + \ldots + RPN_{Failure\ Mode\ n} \tag{2}$$

$$RPN_{Subsystem} = RPN_{Component\ 1} + RPN_{Component\ 2} + \ldots + RPN_{Component\ n} \tag{3}$$

Filz et al. [13] developed a data-driven FMEA approach. Again, the failure modes are identified, and the Severity and Detection are determined by interviewing experts in the field. However, the Occurrence is data-driven, factoring in environmental influences as well as usage data and specific profiles. In the study, various maintenance related data sources are linked to each other, which results in a separate database for each damage area and failure mode. This database is then used to clean, train and validate a prediction algorithm.

2.3.2 Setting thresholds

Company X has several sensors. For these sensors certain thresholds can be set. If a certain threshold is crossed, Company X can generate a pre-alarm stating something might be wrong with the system.

2.3.2.1 Semi-supervised anomaly detection

Denkena et al. [14] introduce a method in which these thresholds are set with sensor operation data. This is a semi-supervised anomaly detection approach. First, 50 normal processes were run for drilling, pocket milling and circular milling. These processes were monitored with measuring the torque. This data was gathered and collected on a specific time frame. Using this collected data, upper and lower thresholds are calculated for a specific process. When a new process is run it is checked if the torque falls inside the set thresholds. If this is not the case, this is flagged as an anomaly.

A safety factor C determines how wide or narrow the distance between the thresholds are set. Usually, C is lower for critical processes in which it is crucial to have a warning when a failure is coming in. When there are a lot of false alarms, it is wise to increase C so the boundaries are increased.

2.3.2.2 Bollinger Bands

Bollinger Bands (BB) are introduced for investors to monitor stock prices with the use of upper and lower bands based on a shifting moving average [15]. The two most popular averages are the 20- and 21-day averages. This means that the average is calculated based on the last 20 or 21 days [15]. The upper and lower bands are used as indicators for investors when to buy or sell a certain stock. Since the introduction of the Bollinger Bands, not only have they been used for the financial market but also for the industrial sector to detect outliers. For example, Vergura [16] uses the Bollinger Bands principle to monitor photovoltaic systems for anomaly detection.

2.3.2.3 Comparison

Both these models can be used for anomaly detection but advantages and disadvantages come with each model. The created model by Denkena et al. [14] has the main advantage of having statistical robustness. Because the mean and standard deviation are calculated across multiple processes, it ensures that the thresholds are statistically robust and reflects the typical behavior of the process. However, this model is complex and once the thresholds are calculated they are not updated anymore (unless they are recalculated after each process). Moreover, if we want to use this, we need to redefine the model before we can apply it. Finally, the model requires careful parameter tuning which can be hard.

Bollinger Bands are easier to understand and implement. It is a simple method but can still be effective for detecting outliers. The main advantage of the Bollinger Bands is that the thresholds are dynamic, which allows the thresholds to fluctuate over time. However, this model only includes short time measurements which makes the model less robust.

2.4 Failures from Literature

Finding the most important failures in fire sprinkler systems is a crucial step in our research. Therefore, we identify the most common failures in existing research.

Frank et al. [17] have identified multiple component-based studies to construct tables in which the reliability of sprinkler components is documented. Several components have been split up: sprinkler head, piping, system valve, system pump, system water supply and miscellaneous components. We will identify the most common failures by analyzing the tables and looking at the highest failure rate. Frank et al. [17] divides the units into multiple forms such as: failures per demand, failures/year and failures/hour. The failures per demand mainly focusses on the failures that occur when a fire breaks out and when the system operation is needed. Moreover, it is hard to compare this with other units like failures per year. When analyzing the failure, we focus on the highest failure rate. A higher failure rate means that the component will fail faster. Through this analysis, we concluded six failures that are most occurring.

2.5 Component sensors

Hashemian and Bean [18] have documented the parameters related to equipment conditions of typical types of industrial equipment. In their research they explore advanced condition-based maintenance methods for industrial equipment. They constructed a table in which they link various components to sensor data. This table has been reconstructed, so that only the relevant components for fire sprinkler installation are selected. Eight essential parameters are identified that relate to the component's health.

3. Failure analysis of Fire Sprinkler Systems

After reviewing literature sources, a FMEA was conducted with nine service mechanics, two service engineers and one project engineer. This is to find the most common and key failures that occur in a fire sprinkler system. This information is crucial in order to identify what additional data should be gathered, and which sensors are relevant in relation to specific failures.

A FMEA is made out of several important aspects like: components, failure modes, causes and effects. Before we can identify the causes and effects of each failure mode (FM), we must identify the failure modes themselves. A failure mode refers to the specific ways a component or process can fail to perform its intended function. Essentially, it is a description of how something can go wrong. Hence, four semi-structured interviews were conducted with service mechanics to identify the components that have the most failures as well as their failure modes.

Participants were provided with a general components list, where they could indicate which components experienced the most frequent failures. Then, as many failure modes as possible were tried to discover from these components. This was done by repeatedly asking questions how exactly the components failed. For example, when the interviewees mentioned a failure involving only a notification pop-up, we asked about the core of why this notification popped up. This allowed us to gather as many failure modes as possible. Then, it was counted how many times the service mechanics stated that the components were a part of the most frequent failures. Finally, a definitive list was made with the components and their failure modes. For every component on this list at least two service mechanics indicated that this is a component that fails occasionally or a lot.

When the final list of failure modes was identified, interviews with the other five service mechanics, two service engineers and one project engineer were conducted. The purpose of these interviews was to identify the causes and effects of each Failure Mode as well as the Severity, Occurrence and Detection rating.

After identifying the Severity, Occurrence and Detection ratings the Risk Priority Number (RPN) was calculated for every failure mode. Then, the average as well as the highest and lowest RPN were identified. Based on the average RPN ratings, a top 10 of failure modes was constructed. These were the failure modes with the highest average RPN ratings. Furthermore, this top 10 was cross-validated with the failures found in the literature. It was found that some of the failures matched, but there were also some differences. To be consistent, we continued with the failure modes we identified ourselves. Based on the information gathered from the FMEA a relational data model was constructed. This model contains the failure modes as well as the variables/sensors that are correlated to them. This data model helps with identifying the specific failure mode when one/multiple sensors show anomalies.

4. Solution design

In this chapter, our main focus is on creating and comparing two prediction models. Both models set upper and lower thresholds that are calculated using a mathematical model. Moreover, a mechanism is created how the selected model can be updated. Furthermore, missing data is identified for the model to be efficient and accurate. Recommendations for installing additional sensors are provided. Additionally, an explanation is given on how these sensors enhance the ability to predict failures.

4.1 Prediction model

We have created two models. First we discuss a semi-supervised anomaly detection method. Then, we discuss the Bollinger Bands. The two prediction models have four types of outcomes:

True Positives (TP) : The model predicts a failure, and the failure actually happens.

False Positives (FP) : The model predicts a failure, but in reality there is NO failure.

False Negatives (FN) : The model predicts NO failure, but in reality a failure happens

True Negatives (TN) : The model predicts NO failure, and there is also NO failure in reality.

4.1.1 Semi-supervised model

The first prediction model is based on the literature in Chapter 3.2, especially the work of Denkena et al. [14] has been used. From this, the idea of setting upper and lower thresholds as well as introducing a memory factor to include both long- and short-term data has been used.

The model has several essential aspects. When the sensor data was visually analyzed, a crucial discovery was made. Every two weeks, the system gets tested, which is to make sure it is still operating as expected. After this test, the system returns to its normal state, however differences in the mean levels of the sensor data before and after the test were clearly identified. Therefore, the decision was made to divide the data into several periods. A period represents the data from the moment after the system test until the next system test.

The model exists of setting upper and lower thresholds based on the average and standard deviation of the sensor data. When a datapoint falls outside of the threshold, this is flagged as an anomaly. Consequently, a pre-alarm can be given to alert the service mechanics that a failure is expected. A mathematical model is built to explain how we calculate the upper and lower boundaries. The model is driven by three main parameters: δ, θ and C. Parameters δ and θ are inputs for a memory factor. This memory factor combines the global standard deviation gathered from the previous periods and local standard deviation observed in the current period. The parameters influence the weight of the global standard deviation and the local standard deviation while determining the upper and lower thresholds. The safety factor C can be set, to determine how wide the upper and lower thresholds should be. The optimal values for these parameters will be determined by testing the model for multiple setups.

4.1.2 Bollinger Bands

In Section 2.3.2.2 we discussed the Bollinger Bands. This method uses a shifting moving average to calculate thresholds. Again, when a datapoint falls outside of the threshold, this is flagged as an anomaly. Based on an average and standard deviation gathered from the last n days, thresholds get set. Parameter n determines the number of days over which the average and standard deviation are calculated. Increasing this parameter incorporates more days into account, while decreasing it considers fewer days. The model also incorporates a safety factor C. This works the same as in the prediction model in Section 4.1.1; it determines how wide or narrow the upper and lower bounds are set.

4.1.3 Experimental setup

We analyzed and evaluated the two models based on the data of one system and one sensor. First, we discuss the setup of the semi-supervised model. Two Periods have been selected where the data get tested on for both models: Period 4 and TestPeriod. The data from Period 4 is selected because the state is confirmed to be as expected. The TestPeriod however, is selected because of an actual failure. We evaluate the different setups of the models based on how many datapoints (DP) are flagged as anomalies in the TestPeriod and Period 4. Of course, we want to flag as many anomalies as possible in the TestPeriod because an actual failure occurs. However, in Period 4 we do not want to have any flagged anomalies because this is just a normal period. Every 10 seconds, the data is logged and a datapoint is available. In total there are around 110.000 timesteps.

- Semi-supervised model

Periods SS-B1, SS-B2 and SS-B3 are selected as base data. This data serves as our foundation, so we can calculate the thresholds in Period 4 and the TestPeriod. As mentioned, Period 4 and the TestPeriod are used to evaluate the prediction model and to determine the optimal value of the parameters. Again, the data from Period SS-B1, SS-B2, SS-B3 are selected because their state is confirmed to be as expected. The start of the periods represent the day after the system's test. The end represents the day before the next test.

For parameters δ, θ and C we experimented with several different values of the parameters. Experiments are done with 11 different setups, and the parameters for the best setup are chosen. After running all the setups, we analyzed the results and determined the best values for the parameters. When we compare the impact of the different parameters, we see that the safety factor C has the most influence on the upper and lower thresholds. We can really see that when we lower this safety factor, the thresholds get much narrower and the other way around as well. The impact of θ is minimal. When we set θ at a low value, we see that the thresholds get narrow in the beginning of the period. When we increase θ, the thresholds get wider. However, this does not have a huge impact on the thresholds. Lastly, the impact of δ is more noticeable than θ. We see when we set δ very low, the thresholds are fluctuating more. When δ is set higher, the thresholds are more stable and robust.

- Bollinger Bands

For the Bollinger Bands we also select basis data to serve as a foundation for our model. These are Period BB-B1 and Period BB-B2. This data allows us to determine the thresholds based on the complete set of days included in the moving average.

Again, the safety factor C had the biggest impact on how wide or narrow the upper and lower thresholds are set. The parameter n had the biggest impact on how dynamic the thresholds were. A lower n led to greater fluctuations in the thresholds, while a higher n produced a more stable threshold, less influenced by newly incoming data.

4.1.4 Comparison

When we compare the semi-supervised model to the Bollinger Bands, we notice a few differences and similarities. First of all, we see that the best setup of the semi-supervised model outperforms the best setup of the Bollinger Bands. The semi-supervised picked up more True Positives which resulted in a higher score. Moreover, in general the Bollinger Bands are more sensitive to False Positives. A similarity is that in both models, the safety factor is the primary parameter influencing the sensitivity of the upper and lower bounds. The semi-supervised model is in general also more stable. The boundaries do not fluctuate as much as they do in the Bollinger Bands model, unless the parameter n is set very high in that model. Moreover, the semi-supervised model is more tweakable with the input of three parameters in comparison to the Bollinger Bands with an input of only two parameters. Lastly, in time, the semi-supervised model will get more reliable as historical data is taken into account. This is not the case for the Bollinger Bands. Therefore, we make the decision to continue with the semi-supervised model.

We have to be aware that the chosen values of the parameters are trained specifically to detect one failure and to be within the boundaries of Period 4. Therefore, a reliability issue of this research arises. In Section 4.2 we describe how the bounds can be updated as new data is observed and how this increases reliability.

4.2 Updating model

From Section 4.1 we learned that the safety factor is the most important parameter for determining how wide or narrow the thresholds are. Therefore, we solely focus on updating this factor and leave the other parameters out of our updating model. If the safety factor is set very low, this might result in a lot of false positives. On the other hand, if the safety factor is set too high, this might result in a lot of false negatives. Therefore, we create a cost function that updates the safety factor, incorporating the costs and occurrences of false positives and false negatives. The safety factor is then calculated to minimize these costs for the new period. The model can be used after each period to determine the new safety factor. We focus solely on false positives and false negatives as they influence how we should adjust the safety factor. When the costs of the false positives are higher than the costs of the false negatives, the safety factor for the next period is increased. When it is the other way around, the safety factor is decreased. The model aims to find the optimal overall costs associated with these failures. Hence, when more data becomes available, the safety factor approaches it's optimal value and becomes more reliable.

4.3 Additional data

In Chapter 2.2, we defined four types of data essential for conducting predictive maintenance. We review these data types and specify how Company X can collect each type. A framework for documenting was constructed. The framework includes 8 essential elements to document failures well. The framework makes it possible to track the system failures in a structured way. Furthermore, analysis of system failures is easier and more consistent.

4.3.1 Historical data and health/condition monitoring

The documentation of the failure data needs to be consistent. The logs should be filled in properly by the service mechanics and it should be documented in one system. The failed component with its failure mode and effects should all be filled in. This allows for increasingly higher quality logs and historical data. Furthermore, health/condition monitoring data should also be documented properly. When more systems get installed with sensors, the chance of capturing a failure becomes higher. Therefore, Company X would get more health/condition monitoring data.

4.3.2 Load and usage monitoring

In Chapter 3 we have identified the most important failure modes of the components in a sprinkler installation. For each component in our top 10 failure modes, the possibilities for collecting additional data have been reviewed. Based on the literature in Chapter 2.5 and additional specific literature found per component, several recommendations have been given to install or monitor specific sensors. These sensors help in detecting failures and thus increasing the effectiveness of the failure prediction model. First, the variables that are correlated to a component as given in Table 10 were stated. With these variables, additional literature was researched to support the value of a specific sensor. Furthermore, the results from the FMEA were also taken into account. When it resulted from the FMEA that a failure could be detected with a specific sensor, this was included and analyzed as well. From these different methods, we recommended installing sensors on several components. It was found that while some of the sensors were already in place, there were still a number of sensors that had yet to be installed.

5. Results

Classifying failures into different types is crucial because they incur different costs per type. Costs are assigned to every type, based on the travel time and the time to fix a failure. A False Negative incurs the most costs, while a False Positive and a True Positive incurred around the same costs. A True Negative does not incur any costs. A certain number of annual failures is estimated based on insights from the interviews. We evaluate our prediction model using several assumptions. The assumed True Positive percentage level starts at 0%. Then steps of 10% at the time are made, all the way up to 100%. For the additional False Positives, we start at 0, and make steps of 20, all the way up to 80 additional False Positives. For each of these steps, the maintenance costs are calculated and evaluated. Figure 1 shows the costs per True Positive level and additional FP's.

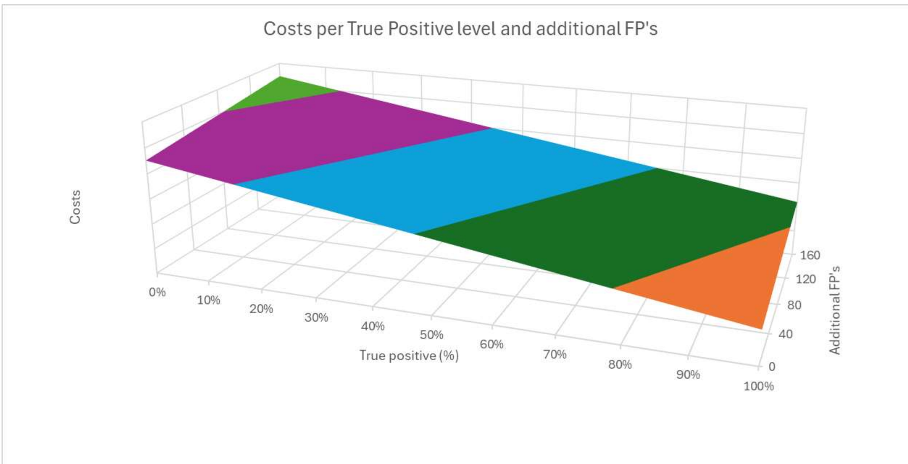

Figure 1: Costs

When we analyze the impact of the True positive level, we can see that when the level increases, the costs decrease. This is logical, since more correct predictions are made and thus the costs decrease. Then, when we look at the additional False Positives, we can see that when less False Positives occur, the costs decrease as well.

However, the costs of a failure are currently charged to the customer. Therefore, when Company X saves these costs through the use of a predictive maintenance model, a loss in revenue is expected. With the use of a predictive maintenance model time will be saved as well. By assuming the number of hours required to serve one system, we can determine how many additional customers can be served using the same number of service mechanics. By estimating the revenue generated by each customer, we can evaluate the break-even points for the potential additional customers and compare this against the number of customers needed to maintain the same level of revenue. Therefore, we review how high the True Positive level of the predictive maintenance model should perform to maintain the same amount of revenue with a certain amount of additional FP's. The following results were found:

- 0 additional FPs: At least 0% TP rate
- 40 additional FPs: At least 6% TP rate
- 80 additional FPs: At least 13% TP rate
- 120 additional FPs: Approximately 20% TP rate
- 160 additional FPs: Approximately 29% TP rate

6. Reliability and validity of research

In this research, different kind of methods have been used to ensure the reliability and validity of the results. Firstly, to ensure the validity of our results, we have constructed the most common and important failures by leveraging existing literature sources and expert knowledge. By comparing these sources, we have already strengthened the validity of our findings. Furthermore, when constructing the FMEA we did not only include service mechanics, but also service engineers and a project engineer. Service engineers and project engineers of the service and maintenance department have encountered failures as well working on their projects. Moreover, they have in-depth understanding of the system design and are aware of the common challenges and solutions of the system. Therefore, including these functions while filling in the FMEA allows for a better reliability and validity of the final results since different perspectives and views are included in the results.

The reliability and validity of the failure prediction model has been established using the available sensor data. However, due to the lack of data, both are not very robust. Currently, we have determined several values for the parameters of the model but we cannot ensure that these values are optimal. This is because the parameters are tuned on only one failure and one good period. Hence, while the current bounds may not yet be fully reliable, we have an updating mechanism in place that enhances reliability as more data becomes available. As new data and additional failure information are incorporated, our model will be better trained, ultimately ensuring greater validity and reliability.

Company X is not the first to implement a predictive maintenance model. Various sectors, such as the manufacturing industry, have already successfully adopted such models. This success validates that developing and implementing a predictive maintenance model is both feasible and valuable.

The selected prediction model is not limited to the fire protection industry; it can also be useful across various other sectors. Any industry that relies on sensor data to monitor and maintain operational processes could find this model valuable for using it to predict failures to ensure optimal performance.

7. Conclusion and recommendations

We can conclude that Company X can transition towards a predictive maintenance strategy. Through interviews and existing research we constructed a list with the most important and occurring failures. Moreover, we constructed a relational data model to identify which sensors are correlated to the different failures. A failure prediction model was developed to detect anomalies in the data, accompanied by an updating model and a framework designed for future use. Following up, several recommendations are given to Company X.

7.1 Recommendations

1. Properly document failures using the provided framework

Effective documentation of failures has not always been consistent at Company X. When transitioning to predictive maintenance, it is crucial to adopt a standardized documentation method. This ensures easier data analysis and results in more reliable outcomes. Therefore, we recommend using the provided framework for documenting these failures.

2. Implement failure prediction model

Currently, the failure prediction model is implemented in VBA. However, when real-time predictions are the goal, this is not attainable. For this research, we have extracted the data manually from the cloud. It is recommended that Company X streamlines this process, so the data of the cloud gets analyzed automatically with the failure prediction model. Additionally, it is advised that Company X logs the system tests, allowing for the definition of multiple periods. These periods can be used to further train the model and enable the prediction model to filter out the wrong data automatically. Furthermore, the current value of the parameters should not be considered final. We have an updating model for the safety factor, however for the other two parameters more experiments should be run to find the optimal values when more data becomes available.

3. Further develop relational data model

The relational data model helps in identifying the failures based on the status of the sensor data. When multiple sensors are above or below the thresholds, anomalies are detected. With the relational data model, the possible failure modes can be in/excluded. However, this data model is not final and should be updated. If the new incoming failures are properly documented, the relational data model can be updated. This improves the effectiveness and reliability of the data model and can be valuable for future identification of the failure modes.

4. Implement additional sensors

To improve the effectiveness of Company X ’s prediction model, it is recommended to implement the additional identified sensors for each component. Adding these sensors will enhance the accuracy and reliability of the prediction model.

7.2 Limitations

In this thesis, several assumptions are made which may impact the reliability and validity of the research. Additionally, there are several other limitations of the research. We will go over them and explain how much of an impact they have on the final results.

The biggest limitation of the research is the lack of data. This has an impact on both the reliability and validity of the failure prediction model. This has been discussed in Chapter 6.

The lack of data also had an impact on determining the most occurring and important failures. Instead of quantitively determining these failures (i.e. using logbooks), we have determined these by conducting semi-structured interviews. Given the number of experts we have interviewed, we can say that these predictions are quite reliable. However, it should be said that when the failures get documented properly over the next few years a quantitative analysis is not superfluous. This increases the reliability and validity of the most common and important failures.

It is assumed that the predictive capabilities of the model lead to a reduction in repair and travel time to solve the failure. Optimizing the scheduling of the service mechanics was not in the scope of the research, however it should be taken into account that this is necessary in order to achieve these reductions. Efficient scheduling ensures that service mechanics are deployed in a manner that maximizes their availability and minimizes travel time. Depending on how well these aspects get implemented, the actual reductions can of course deviate from the expected reductions. Consequently, this has an impact on how much maintenance costs can be saved and how many additional customers can get served using the same number of service mechanics.

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