Robustness evaluation of dynamic maintenance strategies

Henrik Pärssinen

School of Science

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Supervisor

Prof. Ahti Salo

Advisor

MSc. (Tech.) Leevi Olander

Aalto University
School of Science

Aalto University
School of Science

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi
Abstract of the bachelor's thesis

Author Henrik Pärssinen	
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Abstract

Maintenance strategies are crucial to public and private organizations and increasing competition and high tied up capital in equipment and resources have spurred decision makers to seek for more efficient and robust strategies to gain competitive advantage in the market. This has drawn attention to mathematical modeling and furthermore how it can be used in decision making.

This thesis uses the Decision Programming framework in influence diagrams to determine optimal maintenance strategies in terms of costs and performance. Determining the optimal maintenance strategies, the implemented three periodic model takes uncertainties such as condition of the asset and disruptions into consideration. Decisions to conduct planned maintenance and reactive maintenance are made based on these uncertainties. Once the optimal set of maintenance strategies were identified, robustness was studied by perturbing the initial parameters with Monte Carlo simulation.

Using this model the optimal maintenance strategies stayed optimal after the Monte Carlo simulation, indicating studying just the optimal strategies is sufficient when choosing the final strategy. However, when choosing a strategy from the optimal strategies, depending on the preferences of the decision maker, robustness is something that should be taken into consideration as it varied significantly between different optimal strategies. The Decision Programming framework was suitable to model this problem by reason of supporting easy modeling of uncertainties, multiple periods and multiple optimization objectives.

Keywords Decision programming, robustness, maintenance strategy, influence diagrams, uncertainty, decision model

Aalto University
School of Science

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi
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Tiivistelmä

Ylläpitostrategiat ovat olennaisia sekä julkisella että yksityisellä sektorilla. Jatkuva kilpailu, sekä resursseihin ja laitteistoon sitoutunut korkea pääoma on saanut päätöksentekijät etsimään tehokkaampia ja robustimpia strategioita turvatakseen paikkansa markkinoilla. Tämä on herättänyt kiinnostuksen matemaattiseen mallinnukseen ja siihen, miten sitä voidaan käyttää hyödyksi päätöksenteossa.

Tämä tutkimus käyttää ”Decision Programming” viitekehystä ja vaikutuskaavioita määrittääkseen optimaaliset ylläpitostrategiat kustannuksen ja suorituskyvyn näkökulmasta, ottaen huomioon epävarmuudet kuten kohteen tilan ja siihen kohdistuvat häiriöt. Optimaalisten ylläpitostrategioiden määrittämiseksi toteutettu kolmijaksoinen malli tekee päätökset suunnitellusta ja reaktiivisesta huollosta näiden epävarmuuksien perusteella. Optimaalisen ylläpitostrategioiden löydyttyä robustisuutta tutkittiin muuttamalla alkuoletuksia Monte Carlo -simulaation avulla.

Optimaaliset ylläpitostrategiat pysyivät optimaalisina Monte Carlo -simulaation jälkeen, mikä osoittaa pelkästään optimaalisten strategioiden tutkimisen riittoisaksi valittaessa lopullista strategiaa. Kuitenkin riippuen päätöksentekijän preferensseistä, yhtä strategiaa valittaessa optimaalisten strategioiden joukosta, robustisuus tulee ottaa huomioon sen vaihdellessa paljon eri optimaalisten strategioiden välillä. ”Decision Programming” rakenne osoittautui ongelmaan sopivaksi mallinnustyökaluksi, sillä se sopeutuu hyvin epävarmuuksien, useiden jaksojen ja useiden optimointitavoitteiden mallintamiseen.

Avainsanat Decision Programming, robustisuus, ylläpitostrategia, vaikutuskaavio, epävarmuus

Contents

1 Introduction

The continuous economic growth and resulting infrastructural and technological development have drawn attention to asset management. The tied up high capital in equipment and resources has driven organizations to seek for more effective maintenance strategies to asset management problems.

Effectiveness is often measured by objectives such as costs and performance. To achieve maximum effectiveness, the asset management problem should be optimized in terms of these two objectives. This can be done in the case of a single objective or multiple objectives. Whereas single-objective problems are quite straightforward, dealing with multiple objectives, for example minimizing costs and maximizing performance, can be challenging as the comparison between different objectives is not always straightforward (Tian et al., 2012).

Maintenance strategies can be classified into two broad categories, preventive maintenance and condition-based maintenance. Preventive maintenance calls for regularly scheduled maintenance to preemptively counteract future failures, whereas condition-based maintenance relies on observing the condition of the asset to decide whether maintenance activities are necessary. (Tsang, 1995)

Maintenance is often done to prevent failure, but regardless of the maintenance strategy, failures may still occur. An asset failure can be caused by the condition of the asset, but also by an unexpected external load factor. External load represents uncertainties of external conditions affecting the asset. These uncertainties could be environmental concerns such as extreme weather or natural disasters, political conflicts or regulatory matters. For an example, extremely cold weather can cause a car's battery to die, causing failure, after which the car needs repair activity to keep performing as desired. With multiple periods, external loads can be correlated. In the car example, for instance, considering a period of one day it is likely that subsequent periods have similar weather conditions contributing to similar levels of external load.

Analyzing external loads is important as above mentioned risks can otherwise be neglected. However, estimating the levels of external load is not always trivial. Many of the factors that contribute to external load levels cannot be predicted. For example earthquake prediction turns out to be extremely uncertain due to the complex nature of earthquakes (Kanamori, 2003). This, in addition to the risk-averse management of organizations (Lovallo et al., 2020), makes it of interest to study the robustness of maintenance strategies.

Robustness is a key concept in decision making, as it helps explore the effects that assumptions about uncertainty have on the resulting recommended strategies, especially when dealing with high profile system risks that can potentially cause unacceptable consequences (Baker et al., 2008). For example, failure in a nuclear power plant could cause consequences such as loss of life and unacceptable environmental contamination.

The goal of this thesis is to assess how the relationship between repair and maintenance activities affects the robustness of maintenance strategies. This will be done by first determining the optimal maintenance strategies using the Decision

Programming framework (Salo et al., 2022), after which robustness is studied by sampling a uniform distribution to alter the initial distribution for the external load. This thesis focuses strictly on condition-based strategies on a three period model with known initial asset condition and uncertain external load.

2 Literature review

Maintenance decision problems are not unambiguous. Consequently, there are many different frameworks and models built for solving them (Ruschel et al., 2017). Whenever building a decision model, aspects such as time horizon, risks and optimization objectives have to be determined. For example, if there is a system that has to be running continuously with no down time and the performance of the system does not vary, it may be adequate to just optimize in terms of costs. However, in almost all cases, it is desirable to have a decision strategy rather than just a decision. A decision strategy gives the contingency plan that leads to the final decision, which could give insight to why alternative decisions are not sufficient enough. Also, a decision strategy usually gains more confidence than just a plain decision, as the decision maker gets a broader general view of the solution as well as information about the affecting factors.

2.1 Multi-period approach

A Multi-period approach is convenient as it offers an option to choose the time scale of the model. Single-period models are usually not suitable for long term investors (Mulvey et al., 2003). Additionally, multi-periodic approach allows correlation and communication of information between time periods. For example, instead of evaluating weather forecasts every day, a multi-periodic model allows the forecasts for consecutive days to be correlated. As an example, if the temperature is 0°C today, it will likely be close to 0°C tomorrow as well.

Modeling often relies on discounting to determine the present value of future costs and benefits. While discounting costs is often manageable, benefit discounting may be problematic (Torgerson and Raftery, 1999). Dasgupta (2008) discounted the time value of climate change, finding irreversible events such as climate change are scarcely discountable if at all. In addition to irreversible benefits, benefits that cannot be reinvested, such as health benefits, are hardly discountable (Torgerson and Raftery, 1999). This is why some models do not take time value of resources into account. This can lead to misleading results especially when dealing with long time horizons.

The advantages of multi-periodic models come with a cost, as they often involve more variables and constraints than single-period approaches, thus requiring more computational effort to optimize (Marler and Arora, 2004).

2.2 External load and disruptions

With physical assets, it can be beneficial take into account disruption risks. These disruptions can be caused by external loads, which can be, for example, environmental, political or social in nature(Tsang, 1995), leading to disruptions such as earthquakes, wars or labour strikes, respectively.

A paper analysing disruptions in Asian ports (Lam and Su, 2015) revealed a rising trend among disruptive events associated with external loads. In addition to being difficult to predict, disruption risks are often greater than operational risks (Sawik, 2011). Therefore, while addressing decision problems it is often desirable to also take into account external load that can cause these expensive disruptions.

2.3 Multi-objective optimization

Multi-objective optimization differs from single-objective optimization as there are more than one criteria. In multi-objective optimization, the optimization criteria are often conflicting, meaning that a single optimal solution cannot be determined without some preference from a decision maker (Deb, 2014). This often leads to a set of optimal solutions that are called the Pareto optimal front. In general, multi-objective optimization has greater practical importance than single-objective optimization because almost all real-world optimization problems have multiple conflicting criteria (Deb, 2014).

Lu et al. (2015) discuss the differences between multi- and single-objective optimization methods. In the paper, they optimized renewable energy systems of zero/low energy buildings in terms of CO_2 emissions, total costs and grid interaction index. Combining the multiple optimization criteria into one, single-objective optimization was able to find the "best" single solution directly. However, when optimized in terms of multiple objectives, the decision makers could identify the relationship between the different criteria. This additional information allowed decision makers to make more appropriate decisions.

Multi-objective optimization methods can be categorized into three major categories: a priori methods, a posteriori methods, and methods with no articulation preferences. A priori and a posteriori methods require the decision maker to represent preferences on the relative importance of different criteria. Difference between the two methods depends whether the decisions preferences are taken into account before optimization or after. Methods with no articulation preference do not have the decision maker involved in finding the solution. This usually means determining the whole Pareto optimal front as the optimal solution. In the context of research this is convenient, since the results should be neutral. (Marler and Arora, 2004)

2.4 Robustness

We call a solution robust if it has the ability to tolerate perturbations when numerical parameters are perturbed. Robustness is especially desirable in maintenance decision problems with risks of high profile system failures where consequences overweigh the cost of robustness (Baker et al., 2008). As an example, consider a nuclear power plant. Failure could in this case cause unacceptable consequences such as loss of life and major environmental contamination.

Robustness in maintenance problems has been studied by Zitrou et al. (2013) in the context of single-objective maintenance optimization problems. For sensitivity analysis, they used a concept called expected value of perfect information (EVPI). In addition to the optimal solutions, the study identified the most 'important' parameters in terms of benefit, meaning the parameters that after perturbation most affected the solution.

3 Methodology and results

3.1 Influence diagrams and Decision Programming

Multi-periodic Decision Programming problems can be modeled with an optimization framework called decision programming, developed by Salo et al. (2022).

To utilize Decision Programming, the problem is represented as an influence diagram. Influence diagrams are acyclic graphs $G = (N, A)$ with nodes $N = C \cup D \cup V$. These nodes are chance nodes C which represent uncertainties associated with random events, decision nodes D which represent decision among discrete variables, and value nodes V which represent consequences determined by the realizations of chance nodes and decision made at decision nodes. Let us denote the number of chance nodes as $n_C = |C|$ and decision nodes $n_D = |D|$. The sum of these nodes is $n = n_C + n_D$

Arcs $A = \{(i, j) \mid i, j \in N\}$ represent dependencies between nodes. With arcs we can define the information set of a node $j \in N$ as

$$I(j) = \{i \in N \mid (i, j) \in A\}, \tag{1}$$

This means that information sets are sets consisting of all predecessors of a given node. The acyclic nature of influence diagrams allows the nodes to be indexed consecutively as $1, 2, ..., |N|$, following that for each node $j \in N$ has an information set $I(j)$ consisting of only nodes where index $i \in I(j)$ is smaller than j, i.e., $i < I(j), \forall i \in I(j)$

Each node $j \in C \cup D$ has a finite set S_j of discrete states. A sequence of the realized states of decision and chance nodes $s_j \in S_j, j \in C \cup D$ is called a path. We denote S as the set of all paths. The occurrence of states depends on their information states $s_{I(j)} \in S_{I(j)} = \Pi_{i \in I(j)} S_i$. For chance nodes $j \in C$, this means that each state corresponds to the realization of the random variable X_j. X_j itself depends probabilistically on the states s_i of the nodes $i \in I(j)$ as follows

$$P(X_j = s_j \mid X_{I(j)} = s_{I(j)}), \qquad \forall s_j \in S_j, \quad s_{I(j)} \in S_{I(j)}, \quad j \in C. \tag{2}$$

Equation (2) helps determine the probability of a specific state for each chance node $j \in C$. For decision nodes $j \in D$ the probability of observing a specific state depends on the decisions that are made at each state $s_I(j) \in S_I(j)$.

In Decision Programming, a global decision strategy $Z = (Z_1, Z_2, ...Z_{n_D})$ is a collection of local decision strategies. We denote the set of all decision strategies as

$\mathbb{Z}$. Compatibility between local decision strategy Z_j and path s is determined by

$$z(s_j \mid s_{I(j)}) = \begin{cases} 1, & \text{if } Z_j(s_{I(j)}) = s_j \\ 0, & \text{otherwise} \end{cases}, \tag{3}$$

where a local decision strategy Z_j is compatible with path s if and only if $z(s_j \mid s_{I(j)}) = 1$ for all $j \in D$. This implies that a non-compatible path s with strategy Z occurs with probability 0, whereas if the path is compatible, the probability can be greater than zero.

Using the definitions of paths, states and decision strategies, we formulate a decision problem to a mixed linear programming (MILP) problem as follows

$$\max_{Z \in \mathbb{Z}} \sum_{s \in S} \pi(s) U(s) \tag{4}$$

$$\text{s.t.} \sum_{s_j \in S_j} z(s_j \mid s_{I(j)}) = 1, \qquad \forall j \in D, s_{I(j)} \in S_{I(j)} \tag{5}$$

$$0 \leq \pi(s) \leq p(s), \qquad \forall s \in S \tag{6}$$

$$\pi(s) \leq z(s_j \mid s_{I(j)}), \qquad \forall s \in S, j \in D \tag{7}$$

$$\pi(s) \geq p(s) + \sum_{j \in D} z(s_j \mid s_{I(j)}) - |D|, \qquad \forall s \in S \tag{8}$$

$$z(s_j \mid s_{I(j)}) \in \{0, 1\}, \qquad \forall j \in D, s_j \in S_j, s_{I(j)} \in S_{I(j)} \tag{9}$$

The objective function (4) represents the expected utility of the problem, where $\pi(s)$ is the probability of path s for the decision strategy Z and $U(s)$ is the utility of path s given by the decision variable $z(s_j \mid s_{I(j)})$. Constraint (5) ensures that a decision is made at each decision node for all possible information states. Constraint (6) bounds the probability of occurrence of paths $s \in S$. Constraint (7) ensures that only paths compatible with the strategy can have positive probabilities. Constraint (8) ensures that paths with negative utility are fixed to their upper bound $p(s)$. This constraint is not needed if the utility of all active paths is greater than zero. The final constraint (8) limits the decisions to binary variables.

3.2 Constructing and solving the model

The goal of asset management in this thesis is to maximize the performance of the asset with respect to costs. This model considers performance as the operational availability of an asset, which depends on the condition, failure, and repair and maintenance actions of a given period. The performance is portrayed as a percentage of the assets maximum operational availability, meaning that a performance of 50% refers to an asset performing at half of its maximum operational availability.

The initial condition of the asset at the start of period one is known, and the condition can change during each period. After each period the asset manager has an option to maintain the asset for a fixed amount of 50000€ to potentially improve its condition and consequently the performance.

The asset is also affected by external load that contributes to the probability of failure. The level of external load of a given period is always dependent on the external load of the previous period. The asset manager can choose to repair the asset for a fixed amount of 25000€ to counteract the failure and improve the condition of the asset as well as the performance. An asset that has failed and is not repaired will have performance of 0 for that period.

Taking external load into account in the above described setting is desirable because the asset condition alone is often not enough to determine the probability of failure. As an example of unforeseen external load, the recent Russian invasion of Ukraine has caused disruptions (failure) world wide in the forms of increasing energy prices, broken supply chains and overall market depreciation.

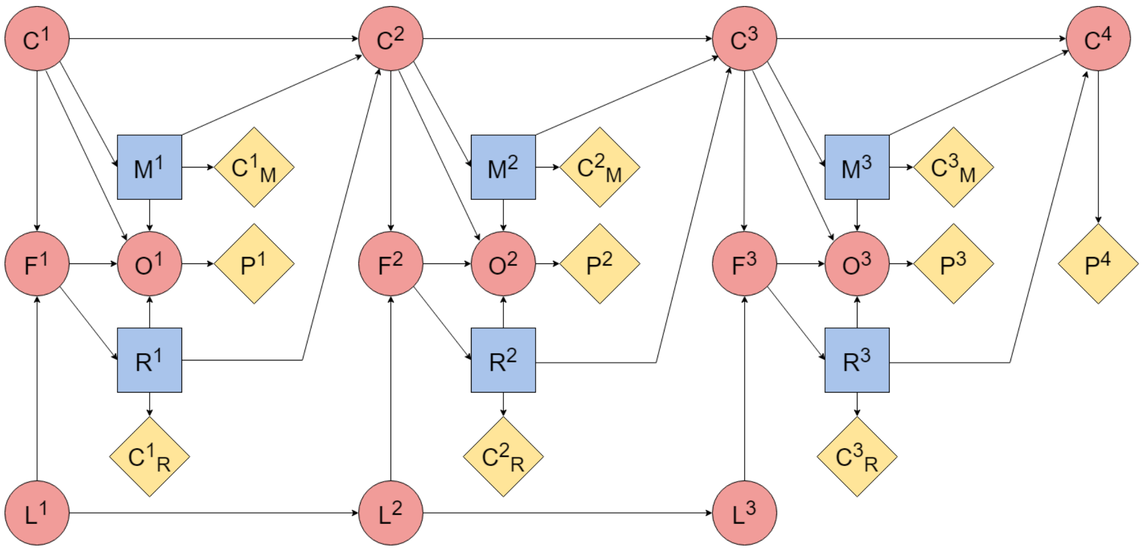

Figure 1: The influence diagram of the problem setting

Table 1: Statespaces S_j for each node $j \in C \cup D \cup V$ in Figure 1 for time t

Node	States
C^t	{very poor, poor, good, very good}
F^t	{failure, no failure}
L^t	{none, minor, moderate, major}
O^t	{very poor, poor, good, very good}
M^t	{maintain, do not maintain}
R^t	{repair, do not repair}
C^t_M	{0, 50000}
C^t_R	{0, 25000}
P^t	[0,1]

Figure 1 represents the influence diagram of the problem discussed in this thesis. Chance nodes are drawn as red circles, decision nodes as blue squares and value nodes as yellow diamond-like shapes. Similar influence diagram was used by Olander (2022) without the addition that the external loads are correlated. Nodes C^t represent the condition of the asset, F^t the failure state of the asset, L^t the level of external load and O^t the operational availability of the asset. M^t and R^t represent the maintenance- and repair decisions made. Value nodes C^t_M and C^t_R represent the cost for maintenance and repair, and P^t the performance of the asset. The possible realised states of corresponding nodes are represented in table 1.

To reduce the size of the problem, the operational availability chance node and performance value node can be merged into a single value node. As the performance only depends on a single chance node, the simplification is justified without affecting the solutions too much (Herrala, 2020). Figure 2 shows the simplified influence diagram.

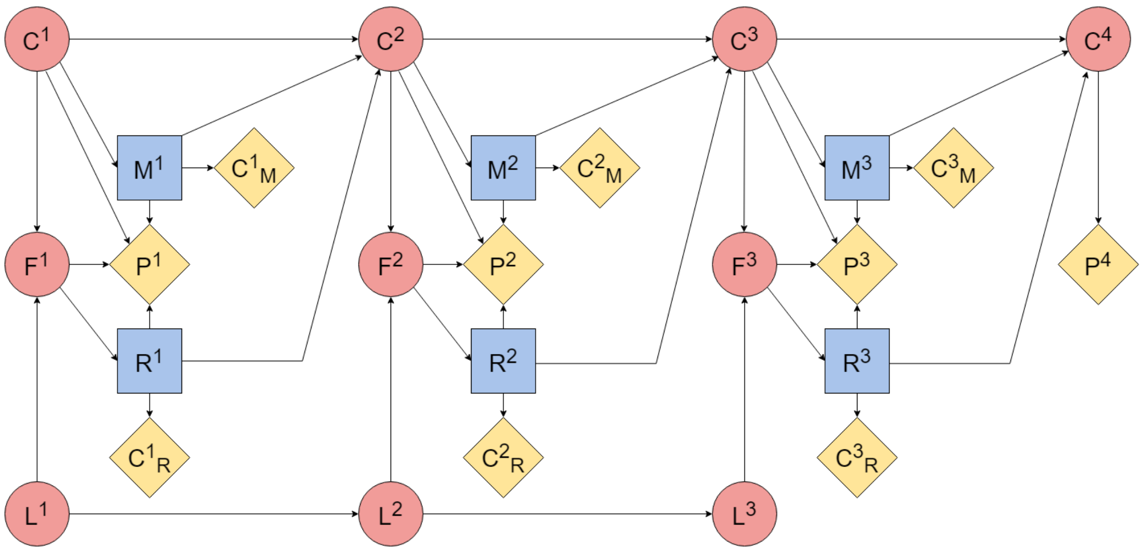

Figure 2: Simplified influence diagram

For this problem setting the total performance and total costs for the path $s \in S$ equal

$$P^{tot}(s) = \frac{p^1 + p^2 + p^3 + p^4}{4}, \tag{10}$$

$$C^{tot}(s) = c^1_M + c^2_M + c^3_M + c^1_R + c^2_R + c^3_R, \tag{11}$$

where p^t is the realized state of node P^t and c^t_M, c^t_R the realized states of nodes C^t_M and C^t_R.

Using equations (10) and (11) and the formulation in Figure 2, the optimization formulation can be written as:

$$\max_{Z \in \mathbb{Z}} \left\{ \sum_{s \in S} \pi(s) P^{tot}(s), -\sum_{s \in S} \pi(s) C^{tot}(s) \right\} \tag{12}$$

$$\text{s.t.} \sum_{m^t \in M} z(m^t \mid c^t) = 1, \qquad \forall t \in T, c^t \in C^t \tag{13}$$

$$\sum_{r^t \in R} z(r^t \mid f^t) = 1, \qquad \forall t \in T, f^t \in F^t \tag{14}$$

$$0 \leq \pi(s) \leq p(s), \qquad \forall s \in S \tag{15}$$

$$\pi(s) \leq z(m^t \mid c^t), \qquad \forall s \in S, \forall t \in T, c^t \in C^t \tag{16}$$

$$\pi(s) \leq z(r^t \mid f^t), \qquad \forall s \in S, \forall t \in T, f^t \in F^t \tag{17}$$

$$\begin{aligned}\pi(s) \geq p(s) + \sum_{t \in T} z(m^t \mid c^t) + \\ \sum_{t \in T} z(r^t \mid f^t) - |D|\end{aligned}, \qquad \forall s \in S \tag{18}$$

$$\begin{aligned}s = (c^1, ..., c^T, l^1, ..., l^{T-1}, f^1, ..., f^{T-1} \\ r^1, ..., r^{T-1}, m^1, ..., m^{T-1})\end{aligned}, \tag{19}$$

$$z(m^t \mid c^t) \in \{0, 1\}, \qquad \forall t \in T, c^t \in C^t \tag{20}$$

$$z(r^t \mid f^t) \in \{0, 1\}, \qquad \forall t \in T, f^t \in F^t \tag{21}$$

where Z is a single decision strategy from the set of all possible decision strategies $\mathbb{Z}$, s is a single path from the set of all possible paths S and $\pi(s)$ is the probability of path s occurring. M is the set of maintenance actions *maintain, do not maintain* and m^t the realised state for period t. R is the set of repair actions *repair, do not repair* and r^t the realised state for period t. The variables c^t and f^t represent the realised states of asset condition and failure. The objective function (12) maximizes expected performance and minimizes expected costs, while constraints (13) - (14) ensure only one maintenance and repair action is taken for a given information state and constraints (20)-(21) ensure maintenance- and repair actions are binary variables. Constraint (19) defines the path. Constraints (15)-(18) bound the path probabilities.

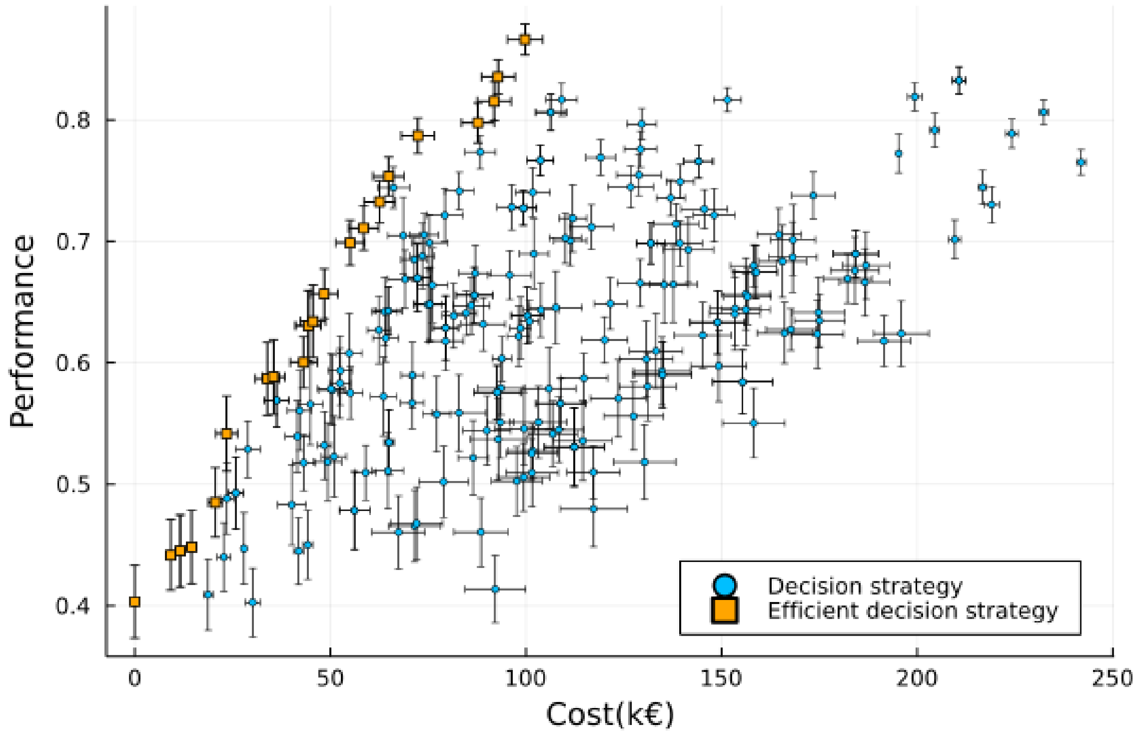

Figure 3: All efficient decision strategies and a random sample of inefficient decision strategies

Figure 3 shows the expected performance with respect to the expected total costs for all efficient decision strategies and for a random sample of decision strategies. The Pareto-optimal frontier of efficient decision strategies was solved successfully and can be seen in the figure. The error bars represent the standard deviation and are scaled to 10% of the actual value for visual purposes. The solutions were found using the Decision Programming framework.

3.3 Robustness evaluation

In this thesis, robustness is studied by examining alternative assumptions to the initial probability distribution of external load. For simplicity, the assumptions considering dependencies between nodes are expected to hold. For example, if the condition of the asset is *very good* and level of external load is *minor*, the probability distribution of asset failure can be determined unambiguously and assumed to hold. In addition, at the start of period 1 the initial condition C^1 of the asset is known without error. Considering the asset is available for inspection this assumption is justified.

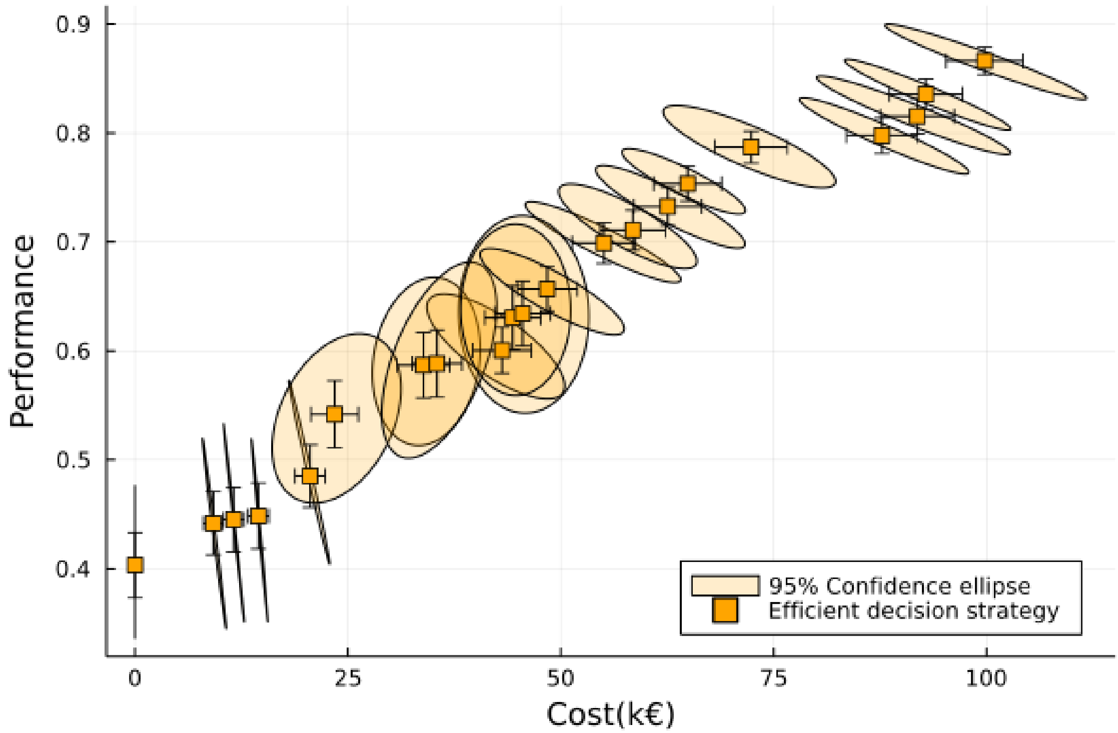

Figure 4: Robustness analysis of all efficient decision strategies

Figure 4 shows the original efficient decision strategies with initial load probabilities of $[0.25, 0.25, 0.25, 0.25]$. The error bars represent the standard deviation scaled to 10% when assumptions on initial external load hold. The 95% confidence ellipses are drawn to visualize the 2D confidence interval on the expected value of both objectives after assumptions on initial external load are perturbed. To find the ellipses, the benefits and costs of all efficient decision strategies were re-evaluated 50 times with first perturbing the initial load probabilities by a random variable following the uniform distribution $\mathcal{U}_{[-0.1,0.1]}$, next normalizing the probabilities to sum up to one.

Figure 4 suggests strategies with lower total costs are highly robust in terms of costs. Thus a strategy with no maintenance or repair actions has zero total costs and is therefore is perfectly robust in terms of costs. Consequently, following a lower total costs maintenance and repair action policy leads to highly unstable performance. When considering high-performing strategies with more aggressive maintenance and repair action policies one should expect more variation in terms of costs, and less within performance. It should be noted that no efficient maintenance strategy uses a policy that maintains and repairs the asset no matter the condition. This kind of policy would be perfectly robust in terms of costs, but as for the problem setting the same or better performance can be achieved without performing both maintenance- and repair actions every period.

Observing the efficient strategies in the middle range with costs ranging from

25k€ to 50k€ and performance ranging from 0.5 to 0.6 reveal the most irregularities in terms of robustness. In general these strategies have broader confidence ellipses indicating greater instabilities. Unlike the low-cost or high-performing strategies, the strategies in the middle range do not have uniformly shaped confidence ellipses, indicating that some strategies with similar costs and performance have differences in terms of robustness. Thus, robustness should be considered when choosing between efficient maintenance decision strategies.

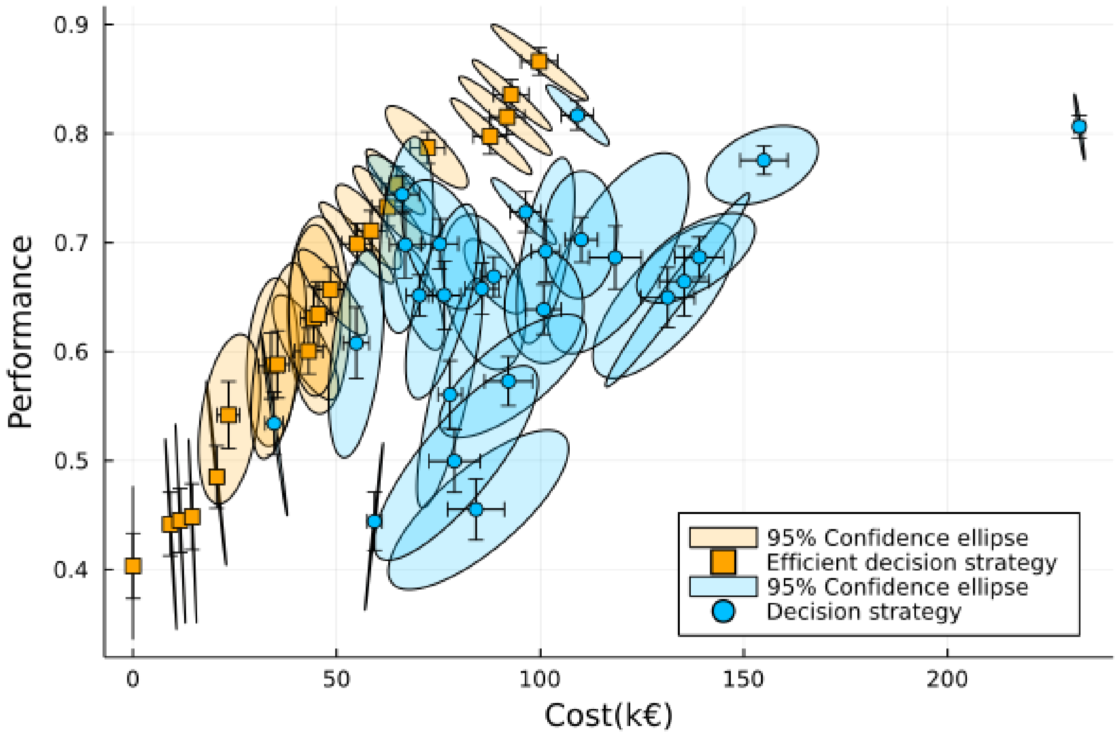

Figure 5: All efficient decision strategies and a random sample of inefficient decision strategies

Figure 5 shows the efficient decision strategies as well as a random sample of inefficient decision strategies. The efficient decision strategies are the same as in Figure 4. The error bars and confidence ellipses were calculated for all the strategies using the same principles as earlier.

It is clearly observed that the confidence ellipses of the inefficient decision strategies are more irregularly shaped. Consequently, when perturbing the original probability distribution of the external load it is harder to predict the behaviour of inefficient strategies without individually analysing the robustness. Furthermore, the confidence ellipses of inefficient decision strategies are noticeably larger, meaning they are generally less robust when compared to the efficient decision strategies. These undesirable properties could be a consequence of the inefficient strategies being less logical and consistent with their decision making, e.g. repairing when there is no failure or not maintaining an asset with bad condition.

Based on this sample, the efficient decision strategies appear to stay efficient after perturbing the probability distribution of the initial external load. The result indicates that it is sufficient to study only the efficient decision strategies when looking for the most desirable decision strategy. Not considering the inefficient strategies when studying robustness turns out to be computationally desirable, because the number of inefficient strategies is substantially larger than efficient decision strategies, e.g. with this model having 21 efficient decision strategies and 262 123 inefficient strategies.

4 Conclusions

This thesis studies the robustness of maintenance decision strategies through a simple multi-periodic approach. Robustness was studied through external load, which was used to model the uncertainties associated with the asset. Perturbing the initial probability distribution of the levels of external load gave instructive results to study the robustness.

According to the results, studying robustness proved worthwhile. Efficient decision strategies with low total costs came across similarly robust in terms of costs and unstable in terms of performance. Furthermore, higher performing efficient decision strategies were robust in terms of performance, but unstable in terms of costs. Most variation in terms of robustness between efficient decision strategies was apparent in strategies that balanced costs and performance. Therefore, it is in the decision makers interest to study robustness especially when adopting a decision strategy that balances between costs and performance.

Another major finding is the persistence of the efficient decision strategies. According to the results, after perturbing the initial assumptions the efficient decision strategies stay efficient. This finding is especially significant as the number of efficient decision strategies is often substantially lower than the number inefficient decision strategies. This result can make further robustness analysis of maintenance decision strategies computationally lighter as the inefficient strategies can be neglected.

The methodology in this thesis is only tested on a simple, illustrative model that makes strong assumptions such as the discretization of all decision- and chance nodes. The model also assumes the cost of maintenance to always be double the costs of a repair action, which may not hold in reality. Due to these assumptions, the results of this thesis should be interpreted with caution. In addition, the robustness analysis conducted is quite brief and leaves room for further research. One objective would be to study robustness between reactive- and preventive-heavy strategies, and examine how the ratio of repair- and maintenance actions affects the final results.

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