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Exploring Future Pricing Strategies for Electric Heavy-Duty Road Freight Services

An exploratory quantitative analysis of pricing strategies for heavy-duty road freight services in a digitalised, electric-only urban environment

Master's thesis in Management and Economics of Innovation / Data Science and AI

LEONARD HEDENBLAD, JOHAN HEGARDT

Department of Mathematical Sciences
CHALMERS UNIVERSITY OF TECHNOLOGY
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Supervisor at Chalmers: Carl Lindberg, Department of Applied Mathematics and Statistics
Examiner: Marina Axelson-Fisk, Department of Applied Mathematics and Statistics

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Department of Mathematical Sciences
Chalmers University of Technology
SE-412 96 Gothenburg
Telephone +46 31 772 1000

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Abstract

The road freight industry is undergoing a transition with the increase in demand for electric trucks and increased digitalisation. The pricing strategies in this industry are still underdeveloped and need reformation. This thesis project aims to: 1. Investigate the implications of various pricing strategies for heavy-duty road freight services in a digitalised, electric-only urban environment, and 2. Provide insights into the development of effective pricing strategies that balance profitability and risk while accounting for the challenges of a future environment with new technologies, cost structures, electrification, and digitalisation.

A methodology that incorporates Multi-Objective Robust Optimisation (MORO) and scenario analysis to identify robust pricing policy alternatives that can withstand different stochastic realisations of both deep uncertainties and well-characterised uncertainties was used. The methodology uses EMA (Exploratory Modeling and Analysis) and EMA Workbench as computational modeling tools to analyse complex systems. The methodology section outlines the research design used to achieve the research objectives. A conceptual XLRM model of the system, with relevant pricing levers and uncertainties, was developed through a literature review and expert opinions from the case company that was collaborated with, which was then translated into a computational model using EMA Workbench. Exploratory research using scenario analysis and feature scoring was conducted to assess risks and benefits associated with each pricing strategy, and sensitivity analysis was used to identify parameters with the greatest impact on outcomes of interest.

The results of the study show that the methodology incorporating MORO and scenario analysis can be used to explore pricing strategies in systems of deep uncertainty. 12 optimal pricing policies were suggested and sensitivity analysis was used to identify features with the greatest impact on outcomes of interest. The study provides insights into potential risks and benefits associated with different pricing strategies in a transportation system characterised by deep uncertainty.

The study concludes that there is no one-size-fits-all pricing policy, there are best performing policies depending on a company's goals and uncertainties. The 12 optimal pricing policies were divided between *dynamic* pricing policies, which are

pricing each customer individually, *flat per km* pricing policies, which are setting a fixed price per km for all customers, and *flat per month* pricing policies, which are setting the same price for each customer. Two of the dynamic pricing policies were found as top-performers, while the only selected flat per month approach seems to be suitable for maintaining predictability of profits and cash flows along with maximising market share and capacity utilisation rate, rather than maximising total profit. Computational models like the MORO approach can be used to explore pricing strategies in deep uncertainty, but decision makers should be cautious of the assumptions and parameters of the model. Future research should explore alternative methodologies and consider behavioral mechanisms in pricing strategies. Overall, this report provides valuable insights into decision making on pricing strategies for heavy-duty electric road freight under deep uncertainty, i.e., in which sort of scenarios different pricing strategies performs optimally and when certain pricing strategies should be avoided.

Keywords: Deep uncertainty, Exploratory Modeling and Analysis (EMA), Multi-Objective Robust Optimisation (MORO), modeling, Python, value at risk, profit analysis, road freight services, electric transition

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List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

EMA — **Exploratory Modelling and Analysis**: A method used in complex systems analysis to develop computational models that simulate the behavior of a system under different conditions and assumptions. EMA is commonly used in policy analysis to inform decision-making.

FTL — **Full truckload**: FTL carriers move freight from the origin location to the destination directly without any intermediate stops. This means FTL carriers dedicate a truck to just one customer for an O-D movement.

ICET — **Internal Combustion Engine Truck**: A diesel-engined truck designed to transport cargo. The truck is driven by a human driver.

MET — **Manual Electric Truck**: A vehicle powered by batteries designed to transport cargo. The truck is driven by a human driver.

MORO — **Many-Objective Robust Optimization**: An optimization approach that simultaneously optimizes multiple objectives and considering uncertainty in parameters to identify robust solutions.

RDM — **Robust Decision Making**: An iterative approach for stress-testing policy alternatives over multiple scenarios, identifying their vulnerabilities and refining them, to produce a more robust set of alternatives for decision-making.

TCO — **Total cost of ownership** : A financial measure that accounts for all costs associated with owning and using a product or service over a specific period of time. TCO takes account not just the initial purchase price, but also ongoing expenses such as maintenance, upgrades, repairs, and replacements.

XLRM — **Uncertainties (X), Policy Levers (L), Internal Models (R), Outcomes (M)**: the XLRM framework in provides a systematic way of structuring information relevant to a system. The framework used in the EMA Workbench involves exogenous factors or uncertainties (X), policy levers (L), relationships inside the system (R), and outcomes of interest (M).

ZET — **Zero-Emission Truck**: A vehicle designed to transport cargo that does not produce any emissions from its power source.

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1
Introduction

This chapter intends to explain the background behind the issue to be investigated in the Master's thesis. Both through the lense of the case company that this thesis is conducted in partnership with and from the perspective of the road freight industry as a whole. Furthermore, it will introduce the aim of the report, as well as the research questions, the thesis limitations and delimitations, and finally ethical considerations and risks will be presented.

1.1 Background

The road freight industry is currently experiencing a transition where 37% of sales of trucks are expected to be Zero Emission Trucks (ZETs) in Europe by 2030 and 100% by 2050 [10]. The development of battery technology, charging infrastructure and policy programs such as the "Drive to zero program", a campaign endorsed by 15 countries with a goal of 100% zero-emission truck sales by 2040, is accelerating the shift to electric [46]. There are also other developments within the industry such as increased digitalisation, investments in data infrastructure and a surge of overall investor interest and startup activity [8].

The changes within the road freight industry could be boiled down into three key developments. Firstly, digitalisation of logistics planning, secondly, electrification of truck fleets and thirdly, the development of autonomous trucks [33]. These developments within the road freight industry has implications for business models and pricing strategies for actors within the industry. According McKinsey & Company (2020)[8], the road freight industry has some of the least mature pricing strategies compared to other industries, but is starting to become equipped to increase economic performance through reformed pricing strategies. Innovative business models and pricing strategies could accelerate the shift from internal combustion engine trucks (ICETs) to manual electric trucks (METs) by reducing the uncertainty of the differences in, for example, the total cost of ownership (TCO) and the value proposition between ICETs and METs [10].

The demand for road freight transport is increasing due to global trade and economic growth. However, carriers are facing challenges in increasing and even maintaining their revenue. The challenges can be classified into three factors: low margins, increased freight costs, and intense competition within the industry. The margin for logistics is generally low in many countries and regions, such as around 4% in the

UK and 1-4% for big European road transport companies. Freight transport costs have been increasing due to rising personnel and fuel costs, resulting in increased prices for transport services. However, higher prices may decrease customer attraction and influence prices in other markets that depend on freight services, making it challenging for carriers to decide on profitable prices. Furthermore, competition is fierce both within the road freight sector, but also between different modes of freight [35].

It is evident that the road freight industry have been lagging compared to other sectors in terms of adopting new competitive pricing strategies. But with the recent emergence of significant investments in digitalisation and new disruptive actors the industry is equipped to explore new pricing strategies and business models [8]. The development of Mobility as a Service (MaaS) business models for electric cars provide useful insights for the development of business models in the road freight industry. While private ownership of electric cars is increasing rapidly, the cost, rate of technological obsolescence, battery life and charging infrastructure issues have suggested that leasing models or shared ownership may be more suitable. Similarly, in the freight transport industry, there is likely to be a shift towards non-ownership models, such as leasing tractor units to operators or charging for services per km or time unit, marking a significant shift from the traditional product-based approach to a service-based model [31]. This change in business model could have a major impact on the sector and new business models has developed such as product-as-a-service models, similar to subscription schemes, and dynamic pay-per-mile leasing of electric trucks [10].

Pricing strategies play a critical role in shaping user behavior and system performance in complex systems such as transportation networks. However, identifying optimal pricing strategies in such systems is challenging due to deep uncertainty, which arises from incomplete knowledge about the system's structure, dynamics, and future trajectories [29]. Deep uncertainty can lead to significant risks and uncertainties associated with different pricing strategies, making it difficult to identify robust pricing policy alternatives that can withstand different stochastic realisations of different uncertain parameters [29] [8]. To address this challenge, this thesis applies a methodology that incorporates Multi-Objective Robust Optimisation (MORO) and scenario analysis using Exploratory Modeling and Analysis (EMA) to explore pricing strategies in systems of deep uncertainty.

This master's thesis is the result of a collaboration with a case company and aims to investigate the implications of various pricing strategies for heavy-duty road freight services in a digitalised, electric-only urban environment. Using a quantitative approach, we have developed a model of the system that considers multiple plausible future scenarios in which the system of parameters and the market for road freight services is influenced by digitalisation and electrification. The aim of the thesis is to explore the potential outcomes of these scenarios and provide insights for decision making regarding pricing strategies in such a future scenario. By leveraging our model and data analysis, we aim to provide insights that can inform the development of effective pricing strategies that balance profitability and risk, while accounting for the unique challenges of a future environment with new technologies, cost structures, electrification and digitalisation.

1.2 Aim

The aim of this research is to explore the outcomes of different pricing strategies for heavy-duty road freight services in a digitalised, electric-only urban environment. Further, it will be explored how a computational EMA model can be developed to analyse the outcomes of the different pricing strategies on the system under different conditions and assumptions regarding e.g. costs, demand, battery range, etc. An evaluation of the outcomes and performance metrics, e.g., the profitability, risk and attained market share of a certain pricing strategy across different scenarios over time will then provide a basis for decision making.
The following research questions were formulated to achieve the aim of the thesis:

1. How can a system representing heavy-duty road freight services in a digitalised, electric-only urban environment be modelled?
2. What pricing strategies for road freight services will be relevant in this system?
3. What risks and benefits are associated with the selected pricing strategies, and how can they be effectively managed?

1.3 Limitations

One limitation of this study is that the model structure and the data collected is applicable for a specific use case, i.e. an urban transportation system in Gothenburg, with case company data on, for example, hardware. This may limit the generalisability and replicability of the findings to other deeply uncertain systems. Additionally, the study does not take into account the biases of the market and decision makers, for example, that customers might prefer certain pricing policies over others, or that decision makers might have preferences for specific outcomes. These limitations suggest that further research with a more qualitative approach is needed to explore how these methodologies can be applied in different contexts and how they can be extended to account for other forms of uncertainty and decision maker preferences.

1.4 Delimitations

This study has been delimited to examining MET transportation services in the urban area of Greater Gothenburg. Hydrogen driven fuel cell electric trucks (FCEVs) are not considered as these trucks are lagging in development compared to METs and are by the case company estimated to not be an efficient alternative for freight in urban traffic in the foreseeable future. Finally, the overall assumptions made in the modelling phase, which can be seen in Table 4, also make up delimitations for this thesis. These are, for example, to avoid the uncertainties of utilisation of each truck and how that will look in the future, the research will only consider fully loaded trucks (FTL). In terms of charging strategy, only depot charging with a 1:1 ratio between truck and charger is considered since it is assumed to be the most feasible approach for this use case [15] [23]. The smallest time unit in the system are months, which entails a delimitation of a monthly even distribution of parameters, even if these might differ across smaller time units in reality. All assumptions will be further elaborated on in the result section 4.1.2.

1.5 Ethical considerations and risks

Bell et al. [6] affirms the importance of ethical considerations and risks when conducting research. For this thesis project it is mainly valid to consider ethical considerations and potential risks associated with data management. In terms of data management there may be risks associated with the use and storage of sensitive data related to input-data for the model. It is important to ensure that appropriate measures are in place to protect the confidentiality and privacy of this data, and to ensure that it is only used for the intended research purposes [6]. Relevant measures include normalisation of data and the anonymisation of entities such as organisations and individuals.

2

Theory

In this chapter, the theory pertaining to the thesis is discussed in order to provide an introduction to the concepts and techniques used in this thesis. The initial section provides a brief outline of systems of deep uncertainty, the second section introduces EMA with subsections on EMA workbench, computational experiments, sampling, optimisation techniques and feature scoring. Finally, relevant research on pricing strategies are introduced which have been used to develop the levers that make up the pricing strategies in the model.

2.1 Systems of Deep Uncertainty

The term *deep uncertainty* originated in the field of model-based decision making and refers to a situation where decision makers are unable to agree on the appropriate models to describe the interactions between a system's variables, the probability distributions to represent the uncertainty of key parameters, or how to evaluate the desirability of different outcomes. Deep uncertainty occurs in situations where there are multiple plausible future states of the world. [29]. From an analytical standpoint, deep uncertainty can be described as the lack of capacity to list various possibilities for the state or outcome of something while without prioritising them based on their likelihood [27].

In contrast to less complex systems, deep uncertainty systems are often difficult to model, predict and/or optimise because they involve multiple sources of uncertainties, such as climate, technological disruptions, geopolitical risks and financial factors. These systems involve a multitude of interrelated variables that can lead to various trajectories of plausible future states of the world [29]. An example of such a system is the future road-freight system, which has many sources of uncertainties, e.g. the power source, energy cost development, battery performance, etc [45].

Dealing with deep uncertainty requires a different approach than traditional methods for dealing with future uncertainty. Instead of relying on probability distributions for model inputs, structure and evaluating outcomes, deep uncertainty requires the development of scenarios, i.e. multiple plausible futures, without assigning specific probabilities to them. Additionally, performance metrics used to evaluate strategies in uncertain systems should focus on *robustness*, rather than identifying the best-performing strategy within a single, most-probable future trajectory [29].

There are distinct dimensions of uncertainty that can be considered. One dimension involves determining the *location* of the uncertainty within the systems analysis framework. According to [27] there are six main locations of uncertainty in model-based decision support:

- System boundary: the distinction between included and excluded phenomena, the context of the system. In this thesis, this is represented by the conceptual model, which is presented in section 3.2, 4.1 and Appendix B.
- Conceptual model: specifies the parameters and their interrelations within the system. The XLRM framework and parameters, presented in 4.1 and Appendix A, is the definition of this in the thesis.
- Computer model: the implementation of the conceptual model in code. The model implementation in Python is the computer model defined in this thesis, see 3.2
- Input data: uncertainty in determining parameter values used as input data in the model. The data collection phase and XLRM parameter data, seen in 3.3., respectively Appendix A discusses these uncertainties.
- Model implementation: uncertainty in implementing the model in code, e.g. bugs and errors. Discussed in 3.2.
- Processed output data: accumulation of uncertainties from data generated in model and post-processing before presenting to decision makers. Discussed in 3.4.

2.2 Exploratory Modeling and Analysis (EMA)

The literature evidences a growing interest in using models to aid decision making when dealing with deep uncertainty. A range of approaches have been proposed, sharing the common goal of using models for exploratory purposes rather than making predictions. The aim of exploratory modeling is to investigate how decision making might be impacted by the currently irresolvable uncertainties by conducting a series of computational experiments that explore how these uncertainties could play out. One of those approaches is Exploratory Modeling and Analysis (EMA) [3]. By simulating scenarios using computational experiments which forms plausible future states of the world based on the models and input parameters, EMA makes it possible to analyse the relations and dynamics of a system in an exploratory manner as well as optimising for suitable policies given desirable outcomes in the simulated scenarios [1].

2.2.1 EMA Workbench

The primary objective of exploratory modeling is to offer computational support for decision making under deep uncertainty and robust decision making. The EMA Workbench is based on EMA and is designed to support the execution and generation of computational experiments and provides means to visualise and analyse the resulting data. It is implemented in Python, based mainly on the SciPy package, and can be utilised to perform exploratory modeling with existing models developed in different modeling packages, including Python, Vensim, Netlogo and Excel. The EMA Workbench enables users to identify policy-relevant uncertainties, evaluate the effectiveness of policy options, and improve strategies in an iterative manner. Additionally, the workbench is designed to support parallel processing on both a single machine and on clusters [26] [13].

EMA Workbench is based on three key ideas: the XLRM framework, the use of simulation models as functions, and a taxonomy of robustness frameworks [13].

Firstly, the XLRM framework in Figure 1 provides a systematic way of structuring information relevant to a system. The framework involves exogenous factors or uncertainties (X), policy levers (L), relationships inside the system (R), and performance metrics or outcomes (M). The EMA Workbench uses this framework to structure the information and explore uncertainties in relationships within the system [26].

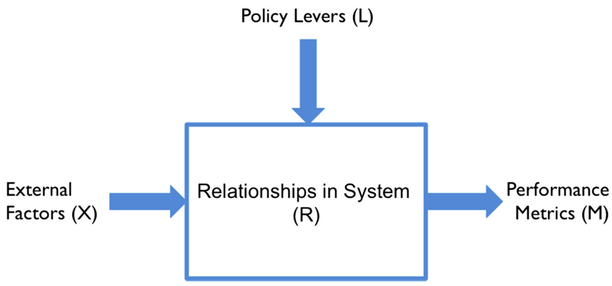


Figure 1: The XLRM framework, collected from Kwakkel et al. (2017)[26].

The second foundation is the use of simulation models as if they were simple functions. The model R can be described as the simple function $M = f(X, L)$. By combining the XLRM framework and the idea of running a simulation model as a simple function, it is possible to explore uncertainties in relationships within the model. This can be done by using a categorical variable to parameterise the uncertain relation, while another approach is to utilise multiple simulation models [26].

Third is a taxonomy of robustness frameworks. This taxonomy includes four components: (1) generation of policy options, (2) generation of states of the world, (3) vulnerability analysis, and (4) robustness evaluation. The workbench can be used for all four components and supports the use of user-specified states of the world [26].

2.2.2 Computational Experiments

In the context of EMA, a single simulation run from a set of models does not constitute a prediction. The key is to avoid trying to predict what is inherently unpredictable. Rather, it serves as a computational experiment that offers insights into how the system would behave if the underlying assumptions about uncertainties in the model were correct. By conducting several such computational experiments, one can explore the implications of different assumptions. The main goal of EMA methodology is to facilitate exploration of the models by evaluating a wide range of parameter values and drawing reliable inferences from them. The results of these experiments can provide valid conclusions that can be employed for decision making purposes [3] [1].

2.2.3 Sampling in EMA Workbench

Using computational experiments to sample the uncertainties from their pre-defined ranges in EMA Workbench creates input variable combinations called scenarios or states of the world. EMA Workbench supports Monte Carlo sampling, Latin Hypercube sampling and Full Factorial sampling, to name a few, as techniques to sample the scenarios [26].

Latin hypercube sampling is a technique used to improve input range coverage. It subdivides the distribution of each input factor into equally probable ranges and randomly draws one sample within each range. This is more effective than multiple random draws, which can result in clusters of observations in some parts of the space and a large void elsewhere. To avoid unintended correlation, orthogonal Latin hypercube designs reorder draws in each dimension. No consensus exists on the best design, but one simple method is to sequentially generate multiple possible orderings and select the ordering that minimises maximum correlation with previous dimensions' draws [20].

A Latin hypercube design of experiments is advantageous over the factorial or grid-based design when dimensionality of input parameters in the models will be high and computational resources limited, because every experimental observation provides useful information, even when input factors are unimportant or spurious. This is because every experiment is unique in each input dimension, whereas a factorial grid is likely to have data points simply replicating others which will not add any useful information and increase computation time [20].

2.2.4 Many-Objective Robust Optimisation (MORO)

Decision making and planning in complex systems of deep uncertainty may involve multiple actors with competing preferences and diverging beliefs about the future. The Robust Decision Making (RDM) method proposed by Lempert et al. (2006) supports decision making under deep uncertainty [37]. The search for robust policies involves finding policies that are resistant to changes in uncertain parameter values. Although the optimal policy may belong to the set of robust policies, it is more common for robust policies to be suboptimal under any individual state of the world. The robustness of a policy can be evaluated from multiple perspectives, such as resistance to change, avoidance of change, recovery from change, and adaptability in response to change. Established robustness metrics, such as optimising percentiles of the outcome data, prioritise these different perspectives and involve calculating the outcomes of interest or performance metrics for a set of decision alternatives and possible future scenarios. The search for robust solutions requires evaluating potential solutions over a large ensemble of scenarios, which cannot be represented by a small number of possibilities due to the large amount of uncertainty. Instead, large ensembles of potential futures are used, with the number of scenarios ranging from a few hundred to several million [4].

The identification of robust strategies that provide acceptable performance across multiple objectives is crucial in supporting decision making under deep uncertainty. Various RDM methods based on EMA have been developed to achieve satisfactory performance across multiple possible realisations of deep uncertainties, including Many Objective Robust Decision Making (MORDM), Multi-Scenario MORDM, and Many Objective Robust Optimisation (MORO). Selecting the most suitable RDM for finding robust policies is mainly a trade-off between robustness metric performance and computational cost. In a case where a large set of scenarios and lever combinations are available and no policies are pre-defined, MORO is the option that evidence suggests may find the most robust policies. However, it also has the highest computational cost. MORO considers a set of scenarios and optimises the robustness of strategies over this set of scenarios, unlike MORDM and Multi-Scenario MORDM which optimise for a single scenario or a limited set of scenarios. The literature suggests that optimisation solutions for a specific scenario may not perform well in other scenarios due to the price of robustness. To include robustness considerations in the search phase for candidate solutions, MORO uses a sampling approach to generate a test set of scenarios. The robustness of candidate solutions is then evaluated using an ensemble of scenarios, and for each outcome of interest, an aggregation function is applied over the performance in each scenario to obtain a single robustness score. MORO has been successfully used in various studies, including identifying the Pareto approximate set of robust policy pathways for climate adaptation and finding appropriate signposts and triggers for an adaptive energy transition policy. By using MORO, it is possible to develop a robust set of policy alternatives that can withstand different stochastic realisations of both deep uncertainties and well-characterised uncertainties, thereby supporting the decision making process for complex systems [4].

2.2.5 Many-Objective Evolutionary Algorithms (MOEA)

The objective of MOEAs is to identify Pareto approximate set in a multi-objective space. EMA Workbench utilises the research of Bartholomew and Kwakkel (2020) to implement a generational version of an algorithm, called BORG, integrating auto-adaptive operator selection, adaptive population sizing, and restarts into the so-called ϵ-NSGAII algorithm. The generational version of BORG is motivated by the slower convergence of steady-state algorithms like BORG compared to generational algorithms such as ϵ-NSGAII. The MORO implementation in EMA Workbench is built upon these insights. Bartholomew and Kwakkel determines the robustness per outcome of interest using the domain criterion, calculated by using a set of 50 scenarios sampled from the deep uncertainty space through Latin Hypercube sampling [4].

2.2.6 Feature Scoring

Feature scoring is a set of techniques often employed in machine learning to determine the most relevant features to include in a model, irrespective of the experimental design. These techniques can handle parameters that are real valued, integer valued, and categorically valued. In EMA Workbench, feature scoring is run for each outcome of interest, and it can also be run for a specific outcome if desired, in either regression or classification mode. Extra Trees is one of the most useful techniques in feature scoring when it comes to EMA Workbench applications [26]. It is a tree-based ensemble method for supervised classification and regression problems. The Extra Trees algorithm involves strong randomisation of attributes and cut-point choices while splitting a tree node, which can result in randomised trees that are independent of the output values of the learning sample. The strength of the randomisation can be adjusted to many different problems, and the algorithm is computationally efficient [16].

2.3 Pricing Strategies

A pricing strategy refers to the method that a business uses to set prices for its products or services. It is a means of determining the price level by considering influential factors and achieving certain business objectives. The strategy entails identifying the elements that must be managed to achieve the intended goals. Firstly, this could be the intended pricing objective (e.g. profit maximisation, risk minimisation, market share or even robustness as in the case when dealing with deep uncertainty [29]). A second element is the relative target price-base, for example cost, the market, and/or customer value. A third element to take into account are the internal and external factors (e.g., market environment, in the case of road freight this could be differences between the spot market and the contract market [28]) that the business faces. Ultimately, a pricing strategy is a critical tool for businesses in order to achieve their objectives [24].

There are a plethora of approaches to pricing, Huefner (2015) describes two basic approaches, one being listed prices and the other being quoted prices. Listed prices are ones that are completely transparent to the customer and where in most cases there is not much room for negotiation for the buyer to deviate from the listed price. In contrast, quoted prices are quotas or proposals customised for each specific customer contract. Furthermore, Huefner (2015) presented three primary methods for determining pricing: cost-based pricing, market-based pricing, and value-based pricing. This thesis primarily focuses on market-based pricing, which involves analysing and adapting to the prices charged by competitors, and cost-based pricing, which involves estimating the expenses associated with fulfilling a contract [22].

2.3.1 Cost-based and Dynamic Pricing

As mentioned, pricing can be based on costs or on market prices. The traditional pricing strategy in the road freight industry is based on "cost plus" pricing [8]. This means that the price of a shipment is determined by adding a markup to the cost of the transportation, fuel, and other expenses associated with the shipment. This markup is typically a percentage of the total cost and is used to cover the company's overhead and to provide a profit [12]. The cost base is therefore the determining factor of the price and the cost base in trucking is made up by several factors such as driver wages, fuel costs, truck lease or purchase payments, maintenance, insurance premiums, distance, weight and volume etc [2]. When access to qualitative data becomes more prevalent for road freight companies, each customer can be priced individually using accurate predictions of what costs it will contribute with during the life of a contract. Pricing each contract individually using a cost-based or market-based strategy is referred to as dynamic pricing.

Metrics such as the Total Operating Cost per km or mile is an important metric used in the road freight industry to calculate the total cost of operating a truck, including expenses such as energy, maintenance, and labour costs. Establishing an understanding of the operating costs generated per km can be used to help carriers make informed decisions about pricing [19]. A per mile or per km pricing strategy are common approaches used for FTL road freight services, where the price is based on the operating expenses per km or mile. On the other hand this approach is not as applicable for LTL road freight services. LTL shipments in general are priced based on their weight and volume, and pricing LTL shipments is a complex process due to the numerous factors that are taken into account [32].

The shift to METs from ICET result in higher capital expenditure (CAPEX), incurred from more expensive trucks and charging infrastructure costs [10]. In contrast to the CAPEX, the operating expenditures (OPEX) of METs are lower than that of diesel trucks. Commercial vehicles such as trucks are used intensively and cover significantly higher mileages than, for example, privately owned cars. As a result, the total cost of ownership (TCO) rather than the initial purchase price becomes the most important factor for transport operators [45]. Furthermore, the CAPEX and fixed costs for trucks and chargers might be a more important factor for the cost base, compared to a earlier focus on operating cost per km. Hence, the measure of TCO per e.g. km or time unit, might be the a more relevant cost unit for MET road freight services.

2.3.2 Real-time Pricing Strategies

A real-time pricing strategy involves adjusting prices in real-time based on changes in supply and demand. In the road freight industry, this pricing strategy may be used to, for example, respond to changes in; demand, customers' willingness to pay, competitors pricing, fuel or electricity prices, or other factors that can impact the cost of delivery [36]. By adjusting prices in real-time, logistics providers can respond quickly to changes in the market and ensure that they remain competitive. These pricing strategies is becoming increasingly prevalent in industries with more mature pricing strategies, such as Passenger airlines and E-commerce [8]. The increased availability of demand data, technology facilitating rapid price changes, and tools for analysing demand and market price data are according to Qiao et., al, (2020) [36] the main enablers for real-time pricing. With these developments taking place also in the road freight industry, these pricing strategies might be competitive for road freight companies going forward.

2.3.3 Revenue Management

The concept of revenue management, also known as yield management is mainly relevant in industries with low variable costs relative to fixed costs, hence where a wide range of prices may cover the variable costs [39]. Revenue management initially emerged as a technique used in the airline industry, but is now used in various other industries. The aim of revenue management within the road freight industry is fundamentally to allocate the right transport capacity to the right customer at the right time for the right price. Revenue management could be boiled down into four levers: pricing, capacity control, overbooking, and forecasting. In terms of pricing, revenue management could also be defined as a dynamic pricing strategy, since the technique involve analysing data such as historical demand, current market conditions, and capacity utilisation to determine the optimal dynamic price for capacity. This may involve implementing dynamic pricing strategies, such as offering discounts for unutilised capacity or raising prices during peak periods of demand. Capacity control focuses on maximising revenue while ensuring that allocation of capacity meets customers demand. Forecasting is an integral part of the revenue management technique where the prediction of, for example, future demand, market prices, and capacity has an impact on the pricing and capacity control levers [35].

2.3.4 Flat Rate Pricing

A flat rate pricing strategy is one that involves charging a fixed rate, i.e. a listed price, for a particular service, in the case of road freight that could be pay-per-km or per time unit such as a monthly subscription rate. The flat rate is set regardless of, for example, the specific route, distance (in the case of per time unit), and weight of shipment. A flat rate pricing model provide an easily understood and predictable pricing model for customers. Research indicates that procurement professionals prefer flat rates, even where these are more expensive than pay-per-use options. Furthermore, it can also enable more predictable revenue streams for the carrier having a flat pricing model [25].

In general a fixed subscription fee per time unit results in higher utilisation rates than pay-per-use pricing models, however, a strategy like pay-per-km can offer greater flexibility for pricing adjustments. Subscription pricing can be classified into unlimited subscription and tiered pricing. Unlimited subscription are in general preferred by experienced customers since it provides them with the flexibility to use the service as much as they want without worrying about exceeding any tiered limits. This pricing strategy also reduces their searching and switching costs, as they do not have to continually evaluate different tier options to ensure they are getting the best deal. On the contrary, a small or cost-inefficient service provider usually favors pay-per-use pricing. Additionally, since pay-per-use pricing is more flexible than subscription pricing, customers who may not need the service frequently or who want to test the service before committing to a subscription may be more likely to use it [21].

2.3.5 The Contract Market and the Spot Market

In the road freight industry, carriers can operate on both the *contract market* and the *spot market*. Contract rates are pre-negotiated between shippers and carriers for a fixed period, typically resulting in lower rates than spot rates. Although contract rates provide stability and predictability, spot rates offer flexibility, which is useful for unexpected shipments or changes in demand [28]. In recent years, demand has exceeded supply in all sectors of the trucking industry, resulting in carriers rejecting shippers' loads. This situation has forced shippers to resort to the spot market, where rates have been increasing recently. The spot market operates as an auction mechanism, where shippers put forth loads and carriers bid to fulfill them in near-real-time [47].

When shippers procure road freight services, they typically use reverse auctions to assign carriers to specific routes. The process involves three stages: shippers prepare bids and shortlist relevant carriers, carriers provide quotes, which are typically provided as a rate per mile/km, with a minimum charge or flat rates, and routes are allocated based on cost, performance, and other factors. If carriers reject a load, shippers can use spot markets to post the loads. Spot rates refer to the price quoted for immediate settlement on a commodity or service. Although the road freight industry operates on both the contract and spot markets, carriers' recent refusals of shippers' loads have forced shippers to use the spot market more frequently, resulting in generally higher rates [43].

3
Methodology

In this section the method used to achieve the aim of this thesis and to produce the results in the following section is described. Firstly, the overall approach to research design is described. Secondly, the model creation. Thirdly, data collection and curation and finally the Implementation of MORO on the problem.

3.1 Research Design

This study aims to evaluate various pricing strategies in a deep uncertainty system describing an uncertain future. In order to model such a system, gather the data needed and analyse the results the research should be designed to take into consideration the complexity of deep uncertainty[3]. The research design of this study could be defined as a simulation-based longitudinal study where a market representing heavy-duty road freight services are simulated over a period of 240 months, i.e. 20 years, the estimated lifetime of a charging station, which is the longest constraining depreciation period of the system. However, the study also incorporates elements of comparative and case research design as it evaluates and compares the outcomes of different pricing strategies, respectively focuses on examining a specific phenomenon, in a specific bounded system, (the market for FTL, urban, electric and digitalised freight services in Gothenburg) in depth [6].

According to Bell et al. [6], research can be approached in three ways, qualitatively, quantitatively or a mixed-methods approach. When using only the qualitative approach, decision making relies on personal judgment or past experience with similar problems. Although this approach may be adequate in some cases, a quantitative approach often provides a more structured and logical path through the decision making process, making it a better choice in many situations. However, quantitative approaches require availability of relevant data, which by definition is non-existing in a hypothetical model of the future. A combination of the two approaches in the data collection phase, where ideas of field experts, case company documentation, literature, and external databases form a foundation for best guesses and assumptions in a mixed-method manner. This together with a quantitative exploratory methodology to analyse the dynamics of the system, is desirable for the system analysed in this project. It is therefore imperative to develop a methodology that can account for the deep uncertainty and address the challenges posed by the lack of data, suggests [3]. Further, tools that allows for exploration of the potential outcomes of different pricing strategies under various hypothetical scenarios and incorporation of sensitivity analysis to assess the robustness of the results to changes in key assumptions are needed.

To explore a system such as road freight services in a digitalised and electric-only future characterised by deep uncertainty and complexity, Bankes [3] suggests that the research methodology Exploratory Modeling and Analysis (EMA) can be utilised. The EMA methodology has several advantages over traditional methods that assume a stable and predictable environment. By explicitly considering deep uncertainty and a lack of relevant data, this approach provides decision makers with a more realistic assessment of the risks and benefits associated with different pricing strategies [3]. Additionally, the methodology is flexible and can be adapted to different contexts by changing input parameters and their intervals, making it a valuable tool for evaluating pricing strategies in a wide range of plausible future scenarios.

Table 1: An overview of the 4 main stages in the thesis project.

Stage	**Aim**	**Implementation**
Conceptual modelling	• A systems diagram describing the system's components, and their interactions	• Model created in Miro (see Appendix B) • Applied the XLRM framework • An iterative approach with feedback from experts
Data collection	• Gather data for all XLRM Parameters • Develop sound assumptions	• Literature research • Case company internal documentation and expert opinions • Internal and external databases
Implementation of model	• The implementation of the conceptual model in code	• Set up of EMA Workbench environment • Coded in Python • Computational experiments run to test the policies in simulated scenarios of the hypothetical future
Data analysis	• Compare outcomes of different policies. • Analyse pros, cons and risks.	• Using built-in analysis tools of EMA Workbench, which offers both exploratory and optimisation approaches.

3.2 Model Creation

The implementation in EMA Workbench will be based on the XLRM framework, meaning that uncertainties (X), levers (L), internal models, for example, cost, pricing, capacity, market models (R), and outcomes (M) needs to be identified. Throughout the conceptual modelling phase, concurrently with the data collection phase, these XLRM parameters and their estimated intervals based on expert opinions and literature review have been identified.

Developing the system design for this thesis could be divided into two main work streams, the first being developing the conceptual model in the form of a system diagram which is a crucial part of the system design process. The system diagram provides a high-level view of the system, including its components and their relationships, essentially the XLRM parameters, and helps to ensure that the system is designed to realistically represent the market of electric, digitalised and urban road freight transportation. The model has been validated by case company experts. Implementing the conceptual model in code is the second part of the system design process for this project. Once the high-level architecture and components of the system was defined in the conceptual model, they need to be translated into actual code so that simulations can be executed on a computer. This involves selecting the appropriate programming language, tools, and frameworks to implement the system design.

3.2.1 Conceptual Model Development

Conceptual modelling involves describing the underlying semantics of software systems and applications at a high level of abstraction. The main goal of conceptual models is to create a blueprint for the system that captures its structure, behavior, and interactions in a clear and concise way. To achieve this conceptual modelling comprise identifying the entities, relationships, and constraints that describes the structure of the system. It can also be used to specify states, transitions, and actions to capture the system's behavior [14].

Creating a conceptual model representing the system to be analysed has several benefits. One major benefit is that it helps visualise the system in a high-level view from which one can ensure that all stakeholders in the project have a common understanding of the system's functionality. Based on an iterative development of the model in the form of a system diagram and feedback from stakeholders at the case company, issues could be resolved at an early stage of the study. Furthermore, it facilitated the design process to ensure that the model includes all the necessary parameters to represent the system, but also to delineate the system to ensure that it doesn't become exceedingly complex. Throughout the process of building an overall understanding of the system the conceptual model also served as a basis for communication with stakeholders in different roles at the case company and university supervisors [14].

During the iterative development of the conceptual model in conjunction with the data collection phase, certain assumptions were made. The rationale behind this approach was to avoid creating a system that was overly complex and difficult to model and implement in code, while still producing reasonable outputs.

Additionally, since EMA is an exploratory methodology, it allows for a wide range of scenarios to be analysed rather than just focusing on the most plausible scenarios for the future development of specific parameters. As a result, the investigation of different types of edge cases is possible. An EMA expert at the case company noted that it is also best practice to disregard clearly non-valid scenarios during the analysis phase rather than during the modelling phase.

The development of the conceptual model took place in the tool Miro where four major iterations of the model eventually led to a final version, which can be seen in Appendix B, this was then implemented in Python. Miro could be defined as a virtual whiteboard which makes it a suitable tool for collaboration and stakeholder feedback [30].

3.2.2 Model Implementation

After conceptually modelling the system of interest, a model in Python was created according to the understood relationships between uncertainty and outcome data as well as internal data used for calculations. Poetry was used for dependency management and for developers at the case company to be able to run the model in their own environments as smoothly as possible [34]. A full list of packages can be found in Appendix F. The model was coded, and all computational experiments run, on a Macbook Pro with 16 GB LPDDR5 RAM Memory and an Apple M2 8 (4 high-performance, 4 high-efficiency) core processor with an integrated 10 core GPU.

3.2.3 Model Validation

Bell et al. [6] define three key criteria for evaluating research: reliability, replicability, and validity. Reliability refers to the consistency and trustworthiness of results and measures over time, while replicability is concerned with whether a study is capable of being replicated by others. The third criterion of validity concerns the integrity of the conclusions generated from the research. There are several types of validity, but two that are of main concern for this thesis: measurement validity, which asks whether a measure captures the phenomenon it is intended to capture, and internal validity, which is concerned with whether a conclusion that incorporates a causal relationship between variables is genuine or produced by something else.

In terms of the reliability of this thesis project, the XLRM data collected and used as input data in the model to generate scenarios rely on current assumptions from both the literature and the case company experts, which may diverge from the actual trajectories that develop in the future. This is particularly true given that as the technology and road freight industry continue to develop, the level of uncertainty will decrease, and consensus around a more specific trajectory might establish. This might make some of the explored future trajectories in this thesis less relevant.

Additionally, it may be challenging for other researchers to reproduce the study due to the anonymisation of the case company data. However, we have normalised the data and maintained the same relationship between input variables as provided by the case company, but re-scaled. Other researchers will not have access to the anonymous data, however, they can rely on the consistency of the input-output relationship presented to the case company. Moreover, readers can replicate the experiment by using different input assumptions and generating their own results with the same model, without knowledge of the data presented to the case company, ensuring replicability. Therefore, the relationship between input and output is replicable, as are the results, while the specific data presented to the case company remains anonymous.

Measurement validity in the case of this thesis is concerned with whether the data collected and the model developed accurately captures the phenomenon being studied. The phenomenon in this case is to identify relevant pricing strategies and explore the benefits and risks of these strategies for electric and digitalised heavy-duty road freight services. To ensure measurement validity, we have carefully selected and evaluated the sources of data used as inputs in the model, as well as conducted extensive literature review, in parallel with case company expert feedback. This has ensured that our measures are consistent with previous research in the field while also being applicable to the case company specific situation. We have also employed rigorous data cleaning and preprocessing techniques to minimise the risk of measurement errors. For example, this was done after implementation, where the dynamics of the programmed model was experimented with using tests generated by GitHub Copilot [17]. The GitHub Copilot extension in Visual Studio Code helped create test data, including edge cases, of the system as a whole. Afterwards, manual tests were conducted where a data set was followed from start to end of the model computations, and by comparing to a real case from the case company it was a suitable strategy to find potential bugs.

Finally, examining the causal relationship between variables is an integral part of the results of this thesis. Hence, internal validity, which concerns whether the causality between variables actually exists, can be considered as key concern for this thesis study [6]. To address this, statistical techniques such as feature scoring, seen in Appendix E, has been used to identify and test the causal relationships.

3.3 Data collection and Curation

The data collection stage of the project consisted of collecting data for all of the parameters in the XLRM framework and for assumptions within the system. The data collection sources used in the project could be divided into two categories; 1. *internal case company data and expert opinions* and; 2. *external data from literature* *studies and open source databases*. In order to make qualified assumptions about the future for deeply uncertain input parameter ranges, a combination of internal and external historical data and projected change trends are used. The rationale for the assumptions made in the modelling and data collection phase relied on case company expert opinions in combination with similar approaches used in research.

The data had to be pre-processed so that it can be used in EMA Workbench. While some historical data will be used as a basis for interpolating into scenarios for the future, some historical data is unavailable and the model will have to rely on expert opinions and literature review about future scenarios and projections for change trends. Furthermore, the data has been normalised to rescale the values of sensitive numerical data to a common scale. The method of min-max scaling between [0, 1] has been applied in this case, which helps to ensure confidentiality by obscuring the raw values of the data. The min-max scaling between [0, 1] was applied to the uncertainty (X) parameters, which needs to be hidden for anonymisation reasons. The scale was later used to re-calculate the outcome metrics to the same scale to preserve the relationship between input and output in the model.

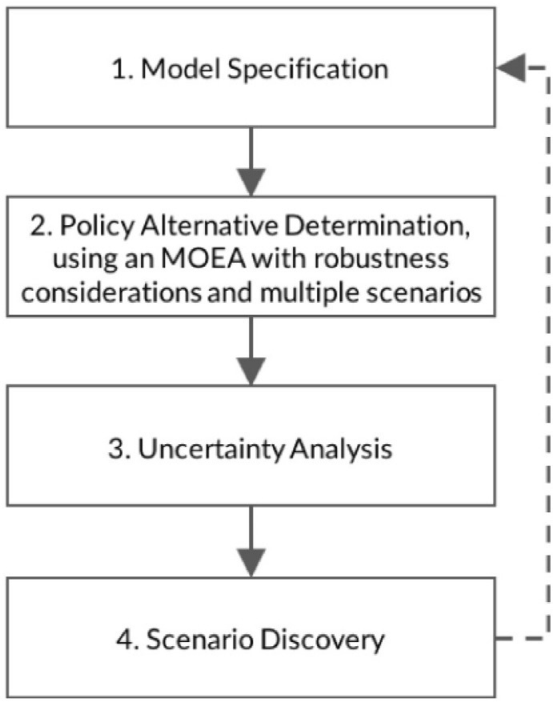
The study uses external input data, such as historical data on freight demand and supply, to parameterise the simulation model. The internal input data was collected by querying the case company's internal databases, which contained comprehensive data on demand, cost base, etc.

The tables presented in Appendix A demonstrate the data intervals used as input data in EMA Workbench. The data is characterised by minimum and maximum values, based on the mean value and case company expert opinions. These intervals were calculated using a combination of external and internal data and models. The approach involves supplying the model with intervals instead of precise values. This aims to facilitate exploratory modelling by covering a broad spectrum of scenarios. As a result, the intervals are quite broad and encompass numerous edge cases.

All numerical data in this report, including means and standard deviations, have been validated by experts from the case company and/or literature. To make the data intervals more relevant for the specific service provided by the case company which is being analysed and to enable applicability for EMA modelling with future projections in mind, some of the externally-sourced data have been slightly manipulated based on the input of case company experts.

3.4 Implementation of MORO on problem

Barthalomew and Kwakkel (2020) recommends implementing MORO on a specific problem according to the workflow in Figure 2. As the model has already been specified previously in this chapter, this section will focus on step 2-4 by defining and elaborating on MORO, parameter selection and choices of analytical tools [4].



(d) Many-Objective Robust Optimization (MORO)

Figure 2: MORO Workflow collected from Barthalomew and Kwakkel (2020) [4].

3.4.1 Pricing Policy Optimisation

EMA Workbench has a built-in MORO function in its Python package, namely ema_workbench.MultiprocessingEvaluator.robust_optimise, which utilises a multi-objective optimisation algorithm to find the Pareto frontier of solutions that trade-off the objectives. It takes into account the uncertainties of the model parameters and generates a set of robust solutions that are resilient to these uncertainties [13]. The optimisation and selection of pricing policy using the finished XLRM model was applied in four steps; Selection of Evaluation Metrics, Defining Robustness Functions, MORO Parameter Selection and Choosing a Subset of Optimal Policies.

3.4.1.1 Selection of Evaluation Metrics

To decide which pricing policies performs optimally, it was necessary to define the metrics for which they will be evaluated. In table 2, the M parameters of the XLRM model are presented. They are all a result of expert opinions at the case company in combination with the theory on pricing presented earlier in the thesis. Together, they result in a combination of slightly contradicting goals and factors that are of high importance for the case company.

Table 2: Outcome parameters of the XLRM model, with which the pricing policies will be evaluated.

Outcome
Avg Capacity Utilisation Rate
Avg Market Share
Avg Profitability
Avg Share Profitable Contracts
Avg Share Profitable Months
Total Profit

3.4.1.2 Defining Robustness Functions

After discussions with the case company, it was found that an optimal pricing policy should maximise total profit over the model lifespan. However, if maximising profits were the only factor to optimise, the optimisation solutions could be a set of risky policies with high variability between and within scenarios. Robustness over the outcomes in Table 2 was the key to success. To find optimal pricing policies, MORO and the ema-workbench Python package was used to determine pricing strategies that would maximise total profit while ensuring robustness under different scenarios. To achieve this, a set of robustness functions were defined as shown in Table 3.

The first two robustness functions aimed to ensure that the pricing strategies would perform well in terms of total profit, both in the best-case and worst-case scenarios. The first function measured the mean total profit, while the second function measured the standard deviation of the total profit share of the mean. The latter function aimed to ensure that the pricing policies would have a low variability and a predictable profit over different scenarios which is of great importance according to the case company.

The next four robustness functions aimed to ensure that the pricing strategies would perform well in terms of different aspects of profitability. The third function measured the 80th percentile of average profitability, trying to maximise the best-case scenarios. The next two functions measured the 20th percentile of the average share of profitable contracts and months. These functions aimed to ensure that the pricing strategies would perform well in terms of consistency in profitability, even under scenarios of low profitability. By maximising the worst-case scenarios, represented by the 20th percentile, it was assumed that policies could avoid ending up in the biggest losses even in negative scenarios. The fourth function measured the 20th percentile of average market share, ensuring that the pricing strategies would perform well in terms of market share even under scenarios of low market share while the fifth function measured the 20th percentile of the average capacity utilisation rate, ensuring that the pricing strategies would perform well even under scenarios of low capacity utilisation.

Table 3: Robustness functions.

Outcome	Max/Min	Function
Total Profit	Max	Mean
Total Profit	Min	Std Share of Mean
Avg Profitability	Max	80th Percentile
Avg Share Profitable Contracts	Max	20th Percentile
Avg Share Profitable Months	Max	20th Percentile
Avg Market Share	Max	20th Percentile
Avg Capacity Utilisation Rate	Max	20th Percentile

3.4.1.3 MORO Parameter Selection

When implementing MORO using the ema-workbench package in Python, appropriate parameters for the optimisation process had to be selected. In this study, the MultiprocessingEvaluator function was used with a number of processes set to the available CPU cores. This allowed for running multiple instances of the model simultaneously, significantly reducing the optimisation time.

To find the optimal pricing policies, the robust_optimise function of the ema-workbench package was used. As described earlier, the robust_optimise function generates a set of non-dominated solutions on the same Pareto front, implying they are equally important in terms of the defined optimisation goal. They represent a trade-off between the different objectives of the robustness functions, and takes the following arguments:

1. robustness_functions: a list of the robustness functions that we want to optimise. In this study, we used the robustness functions specified in Table 3.

2. scenarios: a pandas DataFrame containing the scenarios to be tested. Each row of the DataFrame represents a unique scenario, and the columns represent the input parameters of the model. In this optimisation, 15 scenarios were generated using Latin Hypercube sampling, representing a wide enough spectrum of different scenarios. More scenarios would imply more robust policies but with a higher computational cost.

3. nfe: the number of function evaluations, which determines how many iterations the optimisation algorithm will run. After running 5 individual optimisations with different random seeds and studying the convergence results in Figure 3, it was decided that 5000 function evaluations would be sufficient to find robust policies. Convergence was evaluated based on hypervolume, ϵ-progress and spacing (Reed et al., 2013, Ward et al., 2015). More evaluations would imply a slightly more accurate result with a higher computational cost.

4. epsilons: a list of tolerance levels for the robustness functions. In this study,

the epsilon value was set to 0.05 for each of the robustness functions. A higher epsilon value would result in a more relaxed optimisation process, while a lower value would result in a more stringent optimisation process. By setting the epsilon value to 0.05 for each of the robustness functions, it was ensured that the optimisation process would produce solutions that were robust to a reasonable range of uncertainties in the model parameters.

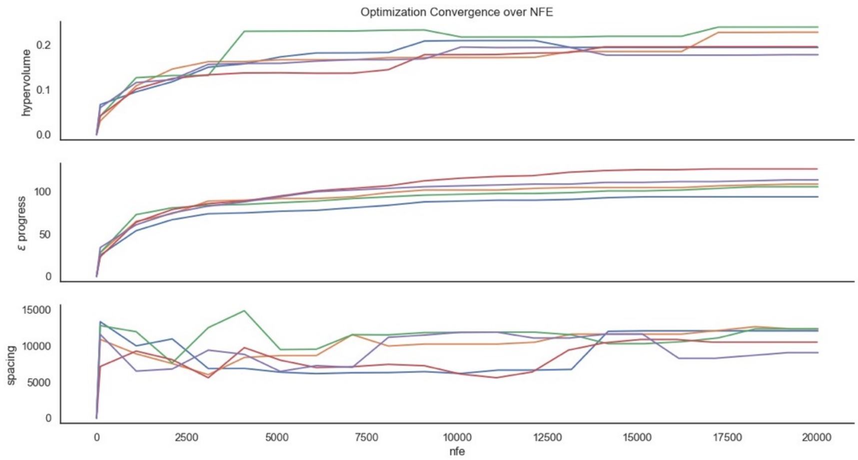


Figure 3: An exploration of the number of function evaluations, nfe, needed for convergence of MORO optimisation for the developed model in this thesis project. Convergence is measured by hypervolume, ϵ-progress and spacing.

The MORO process involves the evaluation of multiple robustness functions and the identification of multiple optimal solutions that are robust across the various functions. The MORO process is stochastic, which means that the outcome of each iteration of the optimisation process may be different due to random factors such as the selection of starting points, the number of evaluations, and the selection of scenarios. In the case of the implementation using the ema-workbench package, the optimisation process uses a Monte Carlo sampling approach to generate multiple scenarios from which to evaluate the robustness functions. This also introduces randomness into the process since the scenarios are randomly sampled from the input parameter space. The specific number of solutions found in a MORO process can vary depending on the number of robustness functions and the complexity of the problem being optimised. Therefore, the final set of optimal solutions should be evaluated and selected based on domain expertise and other criteria beyond just the MORO results [4].

3.4.1.4 Choosing a Subset of Optimal Policies

After generating the set of optimal solutions using the MORO process, the next step was to select a subset of solutions that are both diverse and effective. This is important because having too many solutions can be overwhelming, and having too few can limit the ability to explore the decision space.

To achieve this, a process called Coverage-based selection was used. Coverage-based selection involves selecting a subset of solutions that have different combinations of decision levers and can cover a large part of the decision space while still maintaining high performance measured by the outcomes and robustness functions [9]. This was done by selecting a sufficient number of policies from each category of pricing policy; dynamic, flat/km and flat/month and filtering away similar solutions in terms of lever setup. In addition to coverage-based selection, the subset of solutions was filtered based on policies of interest for the case company which was interested in evaluating new and modern ways of pricing the service. Ultimately, the subset of solutions should strike a balance between diversity, effectiveness, and relevance to the company's goals which are summarised in Table 2.

3.4.2 Policy Evaluation, Uncertainty Analysis and Scenario Discovery

To explore and evaluate the performance of the subset of optimal solutions, 1000 scenarios using Latin Hypercube sampling. Each of the selected optimal policies was run on the same scenarios and the results saved for the following exploration and evaluation steps. The outcome metrics for each of the optimal policies were put together in tables for comparison and evaluation. When evaluating the policies a distinction was made to simplify for future decision making using this research as a basis, by separating profitable scenarios from unprofitable. This means that the analysis will mainly focus on metrics for profitable experiments rather than the total experiment space. The rationale behind this is that when a pricing policy will be deployed in an electric-only future, a lot of the uncertainties of this model will be known to a decision maker. Nonetheless, the negative scenarios are of high importance for measuring value at risk when a decision maker is deploying a pricing strategy in a non-suitable scenario.

The decision maker is assumed to make rational decisions, e.g., it would not deploy a pricing policy with a high market multiplier on a market with high demand price elasticity. In other words, a pricing policy decision maker would not set a price on a service in this manner if customers are known to be unlikely to accept a price which has a large premium compared to the market. Two additional examples are that a decision maker would neither set a flat price with a long horizon on the service if the costs are extremely volatile, and is unlikely to even enter the market if the market itself is highly unprofitable. It is these discrepancies between lever decisions and uncertainty values that are assumed to generate not only the worst case scenarios but also a large part of the unprofitable experiments. A lot of this information will already be available in the results section of this thesis, as feature scoring will show which uncertainties are the main contributors to if an experiment becomes profitable or not, which is described in depth below. Therefore, the analysis of this thesis will be primarily focused on profitable scenarios which tells less about *if* a pricing policy will be profitable or not in a given scenario but instead *how* profitable it would be given that information about the real world is accessible before making the decision. This is mentioned in the methodology section to facilitate for the reader when later interpreting the results.

3.4.2.1 Feature Scoring and Scenario Discovery

The aim with feature scoring was to rank the importance of input features in driving the variability of model outcomes and identify the most influential uncertainty and levers. By prioritising the most influential uncertainties and levers, decision makers can make better-informed decisions and develop more robust strategies. The most influential features may also help discovering scenarios where the policy will perform better or worse. Feature scores were computed for each input parameter, indicating the percentage of the variance in model outcomes attributable to that parameter. The six most influential features were visualised for the model as an aggregate of all policies and then for the outcomes related to each of the subset of optimal policies. For the feature scoring related to finding the features that decides if an experiment becomes profitable or not, all features that had 3% or a greater impact on that decision variable are visualised.

When calculating feature scores per policy, the levers will automatically be disregarded from the ranking as each policy only contains one value of each lever which inhibits a lever comparison between different scenarios. This implies that the total feature scoring provides information about all features, both uncertainties and levers, of the total model while feature scores per policy only provides information about uncertainties. The latter is a way to discover which uncertainties are drivers for positive and negative scenarios for each policy.

Feature scores were first computed for all outcomes and all features using the regression approach described in the theory section. Afterwards, feature scores were calculated only for the total profit outcome with a classification approach dividing the outcomes space in profitable and unprofitable experiments. The feature scores with the latter approach shows which levers and uncertainties are the main contributors to if an experiment results in a positive or negative total profit. All feature scoring and visualisation were performed both for all policies (classic feature scoring) and separately per policy (scenario discovery).

3.4.2.2 Visualisation of Outcome Distributions and Computational Experiments

To further analyse the results of the selected pricing policies, several visualisation techniques were used to gain insights into the distribution of model outcomes across uncertainties and levers. Specifically, the outcome data from all experiments was fitted to Gaussian curves using their μ and σ. The normal distributions for all policies were then visualised in the same plots for later analysis. Further, a random scenario was selected for each policy to visualise the revenue, system cost and variable cost in total. This gives an overview of the cost and revenue development over time in the model. This was also conducted per contract of each month by dividing the revenue, system cost and variable cost with the number of contracts to see how each policy on average priced a contract for that random scenario.

4

Results

The purpose of this results section is to present the findings that answer the three research questions stated in the introduction of the thesis:

- How can the system representing heavy-duty road freight services in a digitalised, electric-only urban environment be modelled?
- What pricing strategies for road freight services will be relevant in this system?
- What risks and benefits are associated with the selected pricing strategies, and how can they be effectively managed?

Firstly, a model representing the system of heavy-duty road freight services in a digitalised, electric-only urban environment will be presented. Then, the findings of the data collection of the XLRM parameters as well as key assumptions for the particular system will be presented. Additionally, optimal policies selected from the optimisation will be outlined. The optimisation resulted in 12 optimal policies divided into *dynamic*, *flat per km*, *and flat per month*. This is followed by an evaluation of the optimised policies using key metrics and outcomes, including value at risk and profitability and more. It was found that especially two dynamic pricing strategies, both based on market price, performed the best in terms of total profit and profitability, but with the cost of higher variance of results. Finally, the section will present the significance of different uncertainties based on the feature scoring of the policies. The choice of *pricing policy* and the *demand price elasticity* were found to be important features for profit variance in general while *truck kms per month*, *company profit margin*, *kWh per km* and *yearly fixed cost change trend* were to varying degrees important after analysing the feature scoring tables for each respective pricing policy.

4.1 The Model Representing the System

The entire conceptual model representing the system of heavy-duty road freight services in a digitalised, electric-only urban environment can be seen in Appendix B. In Figure 4, a simplified version of this system diagram can also be seen. One can comprehensively understand the system's design by examining this simplified model and tracing the downward flow from demand generation through the grey internal models to the green outcomes, such as cost, revenue, and profit creation. This avoids the need to delve into all the internal models, uncertainties and levers displayed in the entire model, while still describing the model as a whole.

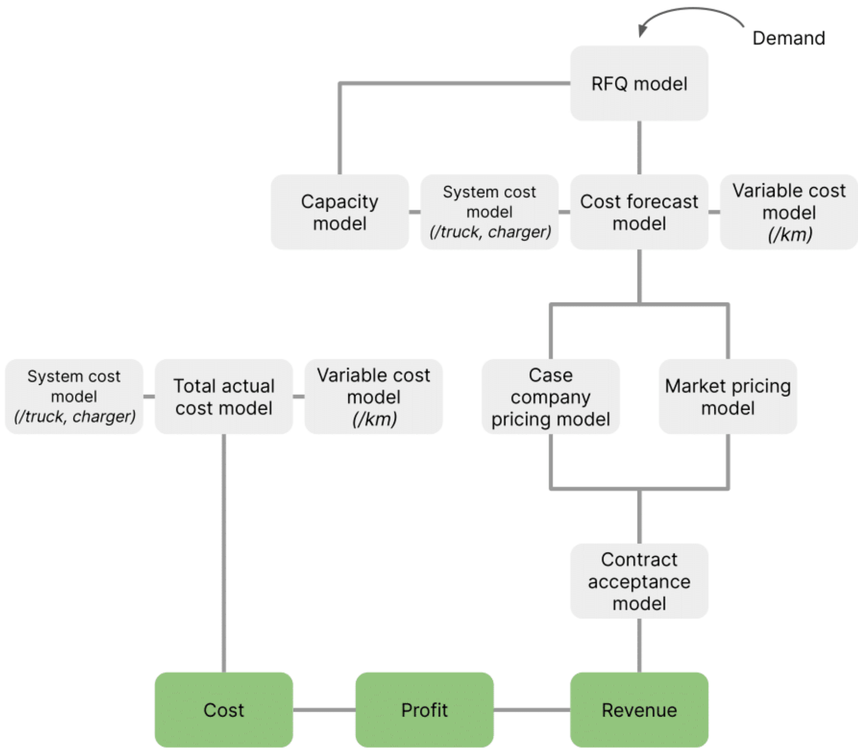


Figure 4: A simplified version of model in this thesis project with the fundamental internal models and outcomes.

The conceptual model representing the system could be described by the following main internal models:

1. **RFQ model:** This is one of the first steps in the system, where the RFQ model first simulates an unsupplied market demand for trucks. The function then generates proposals for customer contracts to fulfill this demand, where the amount of demand being fulfilled using spot contracts and non-spot contracts is calculated based on the current share of spot contracts. For each contract, it generates a contract length t and the contract start and end times, the contract length in kilometers, and the number of trucks needed per kilometer for the contract.

2. **Cost forecast models:** Calculates both fixed system costs and variable contract costs attributable to a certain customer contract. The system costs being all costs related to the system, i.e., unrelated to the number of kms driven which is hardware costs (truck and charging infrastructure). The system cost at time step t is allocated per customer contract based on its km share of total driven kms in t. Variable contract costs are the parameters related to contract costs, e.g. electricity price, labour cost and maintenance cost for the proposed time period. It is worth noting that the level of digitalisation has an influence on the company's and the market's forecasting capabilities.

3. **Capacity models:** Includes models calculating the current (at time step t) available capacity of trucks, batteries and chargers in the system, taking into account replacements and purchases of new capacity needed for newly accepted customer contracts. Purchases of new hardware are assumed to have a lead time of one month.

4. **Contract acceptance models:** Stochastic models deciding if the customer accepts suggested contract price. The case company and the market makes proposals to all contracts on the market and who wins the contract are based on the market's respectively the company's price and the price elasticity of the market in stochastic models. All contracts are assumed to begin one month later, at time step t+1.

5. **Pricing models:** The models that generate the company's and the market's pricing based on the pricing policy generated from the given set of policies or generated from a combination of the policy levers seen in Table 8. Also takes into account repricing of the contracts over different time periods with a certain amount of churn.

All of the internal models developed are described in Appendix A. However these five main models, described above, provides a holistic view of how the system is constructed.

4.1.1 XLRM Parameters

In the tables in Appendix A the uncertainty parameters are listed which represent the (X) in the XLRM framework. The Levers are also listed, which represent the (L) in the XLRM framework. Furthermore, all the XLRM parameters including the Internal Models (R) and Outcomes (M), which have been listed in the methodology section, are described one by one in Appendix A.

4.1.2 Key Assumptions

In table 2 below are the key assumptions for the modelling of the system listed. The general rationale for making such assumptions when creating the model were described in the methodology section 3.3. But the rationale for the specific assumptions will be described here.

Parameter with index 1 was assumed to convert certain parameters such as labour costs per h into per month which is the smallest time step t in the system. 22 days of work/month and 8 hours/day was assumed [7].

For assumption 2 and 3, depot only charging and one charger/truck was assumed for three main reasons. Firstly, literature such as [23] have applied the same assumptions for urban electrified road-freight, secondly this was backed by the opinions of case company experts. Finally it would have made the modelling overly complex and outside the scope of this thesis to delve into charging strategies.

This thesis project was initially delimited to analyse FTL (full truckload) trucks as part of the case company scope and to enable modelling without also accounting for different payloads hence assumption with index 4 was made.

Assumption number 5 was made when constructing the RFQ model, where proposals for customer contracts are generated. In this model all RFQs from customers are assumed to receive a proposal and never a declined RFQ from the case company and the market. *Except* if the Lever "No Short Contract Without Free Capacity" Defined in Appendix A is true for the specific price policy, then the short contracts defined by the Short Contract Time Limit Lever, won't be given a proposal if there is no free capacity (i.e. trucks and chargers to fulfill the contract).

Assumption number 6 states that the market only have a cost-plus pricing strategy. This assumption was made as this is the prevalent pricing strategy within the industry, as mentioned in the theory section, and disruptive pricing policies are in this thesis compared towards the industry standard.

The monthly parameter distribution of the variables in Appendix A is assumed to be uniform throughout each month. This assumption (7) is based on the fact that the smallest time step t in the model is a month, which means that the variables are assumed to remain constant within each month.

Assumption 8 states that the truck data used in the model is specific to a particular truck type used by the case company. This assumption was made to ensure that the model provides accurate and reliable results applicable to the urban heavy-duty truck type. By using specific truck data, the model can account for the unique characteristics of each truck type, such as its average km driven for such a truck, the battery specifications and energy consumption.

Assumption 9 states that delivery lead times for capacity (trucks and chargers) procurement and deployment are assumed to be one month. This assumption helps to simplify the model of when a new customer contract can become operational by assuming a fixed lead time for all capacity purchases.

Assumption 10 states that the maximum battery discharge for the trucks is assumed to be 80% of total capacity. This assumption was made based on the consideration that full discharge of the batteries can lead to increased wear and tear and reduced battery lifespan, which is best practice in the case company.

Assumption 11 states that the model timeframe is set to 20 years. This assumption was made based on an average lifelength of the charging infrastructure, and to ensure that the model captures the long-term effects of the different pricing policies, variability of uncertainties and levers on the outcomes. Additionally, this assumption allows for the analysis of the long-term financial viability of the system and the potential return on investment for the case company.

Assumption 12 states that the primary motive of customer acceptance of contract proposals is price. Price is a key factor in the customer's decision making process, as it directly affects their costs and profitability, especially in the road freight industry where competition is fierce and margins are thin. This assumption facilitates the model development by assuming a single acceptance motive for proposals. However, it is important to note that this assumption may not capture the full range of factors that influence customer acceptance in the market. To somewhat capture other factors, a certain probability is also included, where other motives such as customer relations, service levels, etc. are bundled together.

Table 4: Key Assumptions for XLRM parameters and modelling the system.

Index	Parameter	Key Assumption
1	Operative days/month and hours/day	22 days/month and 8 hours/day
2	Charging strategy	Depot only
3	Number of chargers/truck	1 depot charger/truck
4	Payload	Only FTL
5	RFQ proposal rate	Proposals to all RFQs
6	Market pricing strategy	Only cost plus
7	Monthly Parameter Distribution	Even per Month
8	Truck type	Truck data for a specific truck
9	Delivery lead times	1 month for capacity purchases
10	Maximum battery discharge	80% of total capacity
11	Model timeframe	20 years
12	Customer acceptance motives	Price

4.2 12 Optimal Policies

In Table 5 below are 12 optimal policies, i.e. pricing strategies, chosen from a superset of 196 optimal policies generated through the MORO optimisation for the outcomes described in Table 2. The pricing strategies differ in terms of the set of levers they apply, which generates different outcomes across scenarios. See also Apppendix C for a detailed description of the different lever sets for all 12 policies.

Table 5: The 12 pricing policies to be explored chosen from a set of 196 policies generated through robust optimisation.

Policy	**Characteristics**	**Rationale: P/L**
Dynamic 1	Cost-based pricing with monthly repricing, aiming for a 11.5% margin	**P**: the most profitable dynamic policy in the optimisation with least risk
Dynamic 2	Cost-based pricing with bi-annual repricing, aiming for a 15% margin and spot-contracts being one month	**P/L** : the most profitable dynamic policy with high (50%) premium and (20%) avg. spot contract share
Dynamic 3	Cost-based pricing with annual repricing, aiming for a 15% margin and no spot-contracts (1 month) if no free capacity	**L**: no spot contracts if no free capacity. If capacity is available, it gives a 37.5% discount to increase utilisation
Dynamic 4	Market-based pricing with 1:1 market price ratio and bi-annual repricing.	**P**: best dynamic strategy with market price-base
Dynamic 5	Cost-based pricing with monthly repricing, aiming for a 11.5% margin and has 50% free capacity discount	**P**: policy that provided the lowest standard deviation/risk for dynamic in the optimisation.
Dynamic 6	Market-based dynamic policy with 1.2 market price multiplier and bi-annual repricing	**P/L**: the market-based policy with more than 1:1 market price ratio that has the greatest profit.
Flat/km 1	Three segmented flat pricing and 60% desired market share	**P**: provided the highest profit of all flat policies
Flat/km 2	One segmented flat pricing with 40% desired market share	**P/L**: next highest Flat/km profit and interesting lever set in comparison with Flat/km 3
Flat/km 3	One segmented flat pricing with 100% desired market share	**P/L**: Next highest Flat/km profit and interesting lever set in comparison with Flat/km 2
Flat/km 4	One segmented flat pricing with 40% desired market share	**P**: highest share profitable contracts and months
Flat/km 5	One segmented flat pricing with 20% desired market share	**P**: lowest standard deviation/risk for Flat/km
Flat/month	Monthly flat pricing with two segments and 80% desired market share	**L**: Flat/month generates negative profits, but high market share and utilisation

While there are a multitude of combinations of the 11 different levers, these 12 policies can be categorised into three groups based on their pricing policy lever. The first being dynamic pricing, the second Flat/km and the third Flat/month. The first group comprises six dynamic pricing strategies and the second five Flat/km policies with decisively different lever sets. There is also one Flat/month pricing strategy included, even though it generated less profitable results than the other policies, it may have certain interesting implications for decision making which will be elaborated on in the discussion section. These 12 policies were selected from the pool of 196 policies based on the rationales described in table 3 below. The approach when making this selection was further described in the methodology section. The rationale for including a certain pricing policy is categorised into *P: Performance* and *L: Lever-set*, so either sheer financial/risk performance from the optimisation or the inherently interesting aspects of the lever set for the policy, or a combination.

In Appendix D, one can see how all the 12 different policies perform over a 20 year period for a random scenario. In order to visualise the policies' financial performances in terms of profitability, revenue and the distribution between fixed system costs and variable contract costs in randomly generated scenarios.

4.3 Evaluation of Policies using Performance Metrics

An exploratory analysis was conducted using the EMA workbench to evaluate the potential benefits, profitability, and risk levels of the 12 chosen pricing strategies from the optimisation process. Based on the outcomes of the exploration, performance metrics were generated for each pricing strategy to facilitate for further analysis, including:

- *Total mean profit*
- *Percentage of profitable scenarios*
- *Negative scenarios mean profit*
- *Negative scenarios average profitability*
- *Positive scenarios mean profit*
- *Positive scenarios total profit standard share of mean*
- *Positive scenarios average profitability*
- *Positive scenarios minimum profitability*
- *Positive scenarios maximum average profitability*
- *Positive scenarios share of profitable contracts*
- *Positive scenarios average market share*
- *Positive scenarios average capacity utilisation rate*

The data from the exploration of each pricing policy can be found in Appendix C. To facilitate the analysis, the output data was divided into total scenarios, positive scenarios, and negative scenarios. Total scenarios provides an overview of all the scenarios, while the outcomes for the positive scenarios are the most important metrics for the evaluation of the policies, as motivated in the methodology section. The evaluation of outcomes for the negative scenarios provides additional insights into the risks of each policy.

4.3.1 Profitability

The output data (see Appendix C) indicates that Dynamic 6 is the most profitable pricing strategy over all scenarios with a profit of 158.16, when scenarios are positive it also has the greatest mean profit of 323.49 seen in Figure 5. Additionally, Dynamic 6 has the highest *positive scenarios maximum average profitability* at approximately 31%, and *positive scenarios average profitability* of around 13%. In contrast, Flat/-month is the least profitable pricing strategy, with the lowest mean profit of -562.74, and the lowest mean profit during *positive scenarios mean profit* of 57.96, as can be seen in Figure 5. The dynamic pricing strategies generates greater profits for all scenarios, a similar pattern is seen for the positive scenarios, except Dynamic 1 generating a lower mean profit and average profitability, as well as maximum average profitability.

In terms of probability of generating profitable results, the *percentage of profitable scenarios* is a proficient metric. Where a higher *percentage of profitable scenarios* indicates greater probability in terms of the pricing policy's profitability across the scenarios. Dynamic 3 generates the highest *percentage of profitable scenarios* at 68.7%, closely followed by Dynamic 2 at 68.3%. Then the Flat/km 3-5 policy's and Dynamic 1, 4 and 5 are profitable at around 58-62% of scenarios followed by Flat/km 1-2 and Dynamic 6 in descending order. The Flat/month has the lowest percentage at 2.6%. Furthermore the *positive scenarios share of profitable contracts* also indicate the probability of generating profitable results, Flat/month had the lowest *positive scenarios share profitable contracts* at 59.45%, while Dynamic 6 had the highest at 85.42%, the dynamic policies are slightly better at generating profitable contracts. This suggests that the group of dynamic pricing strategies might be better forecasting costs and setting prices accordingly.

Furthermore, the *positive scenarios minimum average profitability* indicates the lowest level of profitability, as an average over each time step t, that a pricing policy achieves in positive scenarios. Dynamic 6 has the lowest *positive scenarios minimum average profitability* at -27.22%, while Flat/month has the highest at -0.04%. The Flat/km policy's range between -4.63% to -1.99%, while Dynamic 1-5 generates between -3.80% and -25.82%. Hence, for the positive scenarios the dynamic policies can generate some non-profitable time steps (months) in terms of profitability in %, that are by the *total mean profit* (where the dynamic are performing greater than the flat) outweighed by months that bring about large total profits.

4.3.2 Market Share and Capacity Utilisation

Positive scenarios average market share and *positive scenarios average capacity utilisation rate* were outcomes examined for each policy. The flat policies overall induces greater market shares, where Flat/month has the highest *positive scenarios average market share* at 76.91%. Dynamic 6 has the lowest at 22.83%. In between, Dynamic 1 and 4, and Flat/km 1-2 has between 49% to 55% market share. The rest then generates market shares between 35% to 45%.

The *positive scenarios capacity utilisation rate* follows a similar pattern with Flat/-month at the top with 97.49% utilisation and Dynamic 6 being the worst performing with 83.86%. Overall the flat policies generate greater capacity utilisation with Dynamic 4 and 1 as exceptions generating 94.63% and 93.50% respectively.

4.3.3 Risk

However, profitability is not the only factor to consider, as some strategies may be riskier than others. The *positive scenarios standard deviation share of mean profit* metric provides insights into the risk of each strategy. This metric indicates the standard deviations as a share of the mean of the total profit earned in positive scenarios. A higher standard deviation share of mean indicates a higher variability of profit outcomes around the mean, or in other words, the risk of deviating from the expected profit for a certain pricing policy. In this regard, Dynamic 6 has the highest standard deviation as share of mean of 124%, which suggests that the strategy is associated with higher levels of risk. Conversely, Flat/km 1-5 has a standard share of mean ranging between 88%-92%, indicating lower levels of risk. Additionally, Dynamic 1-4 produce even lower levels of risk at 82%-86%. Flat/month 1, the overall least profitable strategy, conversely, exhibits the lowest risk, indicated by the *positive scenarios standard share of mean profit* at 71.8%.

One should also consider the *negative scenarios mean profit* and *negative scenarios average profitability*, which provide insights into the potential risk for losses over scenarios with negative performance for each strategy. Flat/month generates the greatest loss with a *negative scenarios mean profit* at -579.30, and the second lowest *negative scenarios average profitability* at around -14%. On the other hand, Dynamic 6 has the least loss with a *negative scenarios mean profit* at -8.99. Overall the flat policies have greater *negative scenarios mean profit*, however the profitability differs, where Dynamic 5 has the least profitability for negative scenarios of -0.19% and Dynamic 4 the greatest at -0.07%.

The value at risk of each portfolio can be identified by analysing the *negative scenarios mean profit* and *share non-profitable contracts*. The Value at Risk measure indicates the probability for a potential loss of the portfolio of contracts for a certain scenario. For example, for policy Dynamic 6 the portfolio of contracts generates an *average negative profit* of -8.99 with a 50.70% probability, the 50.70% being all non-profitable scenarios for this policy. In terms of value at risk, the Flat/month policy displays the greatest value at risk both in terms of *mean negative profit* and a 97.40% likelihood of the outcome being negative. Following are the Flat/km pricing policies and the Dynamic 4 generating the greatest value at risk among the dynamic pricing strategies. Dynamic 1, 2, 3 and 5 has a more moderate value at risk with a probability of around 30-40% for losses ranging between -101.75 to -160.79.

4.3.4 Concluding Results on the Performance Metrics Evaluation

Figure 5 below illustrates how the pricing policies perform across performance metrics over the positive scenarios i.e. scenarios where the pricing policy generates a profit > 0 over the portfolio of contracts. This can be particularly relevant when analysing the benefits and risks with the pricing strategies as explained in the methodology section. As illustrated by the figure, where on the y-axis we have mean profit and on the x-axis we have the standard deviation as share of mean, the Dynamic 4 policy generates both the second greatest profits and the second lowest risk. Flat/month and Dynamic 6 are essentially each others opposites, where the aforementioned generates low profits and low risk and Dynamic 6 the opposite.

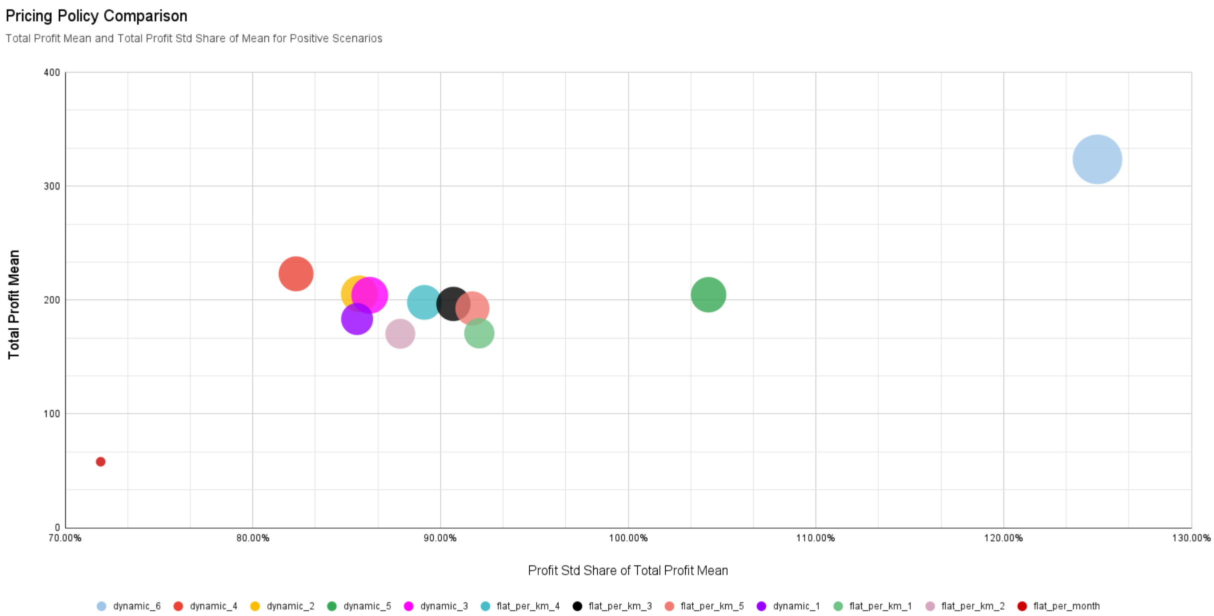


Figure 5: A bubble chart over the *mean total profit*and the *total profit standard deviation as a share of the mean total profit* for the 12 pricing policies. The size of the bubbles represents the average profitability, which ranges from 1.14% for Flat/month 1 to 13.03% per month for Dynamic 6.

The dynamic pricing strategies (Dynamic 1 - Dynamic 6) overall result in higher *average profits*, *percentage profitable scenarios* and *positive scenarios share profitable contracts* compared to the Flat/km and Flat/month pricing strategies. Dynamic 5 and 6 also have a notably higher variability in profitability, as indicated by the

higher values for the *positive scenarios standard deviation share of mean*. However, Dynamic 1-4 have a similar, even a bit lower, *positive scenarios standard deviation share of mean* compared to the Flat/km pricing policies. In other words, the dynamic pricing strategies overall generates greater profits, while both entailing greater risk for some lever sets and scenarios and lower for others. In terms of value at risk, the dynamic policies perform better with lower potential losses and probabilities, except Dynamic 4 which are more similar in this regard to the flat policies.
The Flat/km (1-5) pricing strategies generally have lower *mean profits*, *percentage profitable scenarios* and *percentage profitable contracts* compared to the dynamic pricing strategies. The variability in profitability, as indicated by the values for the *positive scenarios standard deviation share of mean* is similar for all the Flat/km policies, one can see them clustered in Figure 5. This risk metric is greater for the Flat/km policies than the majority of the dynamic pricing strategies. In other words, the Flat/km pricing strategies have a somewhat lower potential for both profits and results in a greater variability of outcomes between scenarios, however, they provide other benefits such as increased predictability of the cash flows.

Finally the Flat/month pricing strategy has the lowest *mean profit* and *percentage profitable scenarios* among all the pricing strategies. It also has the lowest *positive scenarios standard deviation share of mean*, indicating a lower potential for high profits, but also the lowest risk.

In conclusion, this exploratory scenario analysis of the optimised set of 12 pricing strategies reveals some key insights into their profitability, variability and risks. The findings show that some pricing strategies are more profitable and also more risky than others, with Dynamic 6 having the highest *positive scenarios mean profit* and *positive scenarios standard deviation share of mean total profit*, while Flat/month has the lowest mean profit and *positive scenarios total profit* standard deviation share of mean. Overall, the dynamic pricing strategies are the most profitable and have the highest potential for both high profits and less risk. The Flat/km pricing strategies have somewhat lower mean profits variability in profitability. The Flat/month pricing strategy has the lowest profitability and risk among all the pricing strategies.

4.4 Significant Uncertainties and Levers Based on Feature Scoring of Policies

In Appendix E.2, the feature scoring of all policies are presented, both as an aggregated feature scoring of all policies and separate for each. Based on the first feature score of all policies (where both levers and uncertainties are included) it is evident that the choice of pricing policy, i.e. Dynamic 1-6, Flat/km 1-5 or Flat/month has the greatest impact (9.3%) on the outcome *total mean profit* of the pricing strategy. Hence, it is alongside other lever and uncertainty (X and L) parameters very important to choose the "right" pricing policy. Demand price elasticity could be considered as a very influential uncertainty, having the greatest feature score on the average profitability, market share, share profitable contracts and capacity utilisation rate. Other important factors for all policies are truck kms per month, company profit margin, kWh per km and yearly fixed cost change trend.

For the dynamic pricing strategies 1-3, the number of truck kms per month is the most important uncertainty impacting the total profit. Dynamic 4 with a market price-base and multiplier of 1.0 has the market's profit margin as the most important uncertainty for it's profit generation. Demand price elasticity is the most important factor for the Dynamic 5 and 6, even though Dynamic 5 is more coherent in it's lever set to 1-3 it is more similar to the market price-based 4 and 6. The feature scoring of Dynamic 6 43 has demand price elasticity as the only major impacting uncertainty both for all scenarios and only profitable, 56 Overall the factors; truck kms per month, market profit margin, demand price elasticity, kWh per km, yearly total market demand trend, yearly fixed cost change trend, battery lifespan and contract time period have the greatest impact on the dynamic pricing strategies.

The results from the feature scoring for the Flat/km and Flat/month pricing policies is similar to that of the dynamic policies. However, battery lifespan has a greater impact and is a factor in all the flat pricing policies, while only one of the more important uncertainties for Dynamic 1 and 4 across the dynamic policies. Company digitalisation level is another factor, not especially impactful for the outcomes on the dynamic policies, that is important for Flat/km 1-2. It is especially important on the outcomes; share of profitable contracts and months, indicating the impact on cost forecasting by the level of digitalisation. Overall the number of truck kms per month has the greatest impact on total profit for all pricing strategies, with a few exceptions.

Zooming in on only the positive scenarios, the feature scoring displayed in Appendix E.3, shows that demand price elasticity and company profit margin are the two most important factors for generating profitability across all policies. Then truck kms per month, yearly fixed cost change trend, kWh per km, market profit margin and pricing policy in descending order. Worth to note is that it is only in the feature scoring including all policies that the levers are included, as motivated in the methodology section.

5
Discussion

In this chapter, a discussion of the results will be presented, with the aim to offer insights into the three research questions posed. The model created to represent the system of electric and digitalised road freight services will be discussed to emphasise insights related to research question one. Following this first segment, a discussion on the trade-offs between outcomes, divided into profit vs risk, and profitability vs capacity utilisation rate and market share is mainly connected to research question two. While the third segment on discovering preferable and unpreferable conditions for pricing policies, is more related to discuss insights for research question three. Finally, a general discussion on innovative pricing strategies concludes the Discussion chapter.

5.1 The Model of the System

When dealing with a system of deep uncertainty, such as the one in this project, decision makers face difficulties in modeling, predicting, and optimising due to the multiple sources of uncertainties. This is because it is hard to define the appropriate models, probability distributions, and methods for evaluating outcomes when there are multiple plausible future states of the world.

One challenge in modeling the system is finding the right balance between complexity and simplicity. The model created in this thesis project for the system of electric road freight services might be too complex for simple and quick iterations and calculations, see Figure 6, but too simplistic to capture all relationships in the system. The implementation of Figure 4 would have been a more simplistic approach, as it captures only the most important internal models and parameters. To attain relevant results when evaluating the performance of different pricing strategies used in the system, it is crucial to strike a balance between having sufficient parameters to capture relevant factors and keeping the model simple enough to avoid unnecessary complexity and uncertainty. As mentioned in the theory section, uncertainties such as; what power sources will be relevant in the future, energy cost development, battery performance, etc. can have major impacts on the modeling of the system, hence, one has to weigh the benefits of including these factors or not. In this project a model of moderate complexity was created, but a less complex one might have generated similar or even more realistic results. Furthermore, there is dual complexity in terms of, first coping with deep uncertainty regarding future scenarios for the XLRM parameters, then also the fact that modelling the road freight market as it is today is quite complex in itself.

5.2 Trade-offs Between Outcomes

The exploratory analysis conducted using the EMA workbench generated data on the outcomes/performance metrics for each of the 12 pricing strategies chosen from the optimisation. The results provided insights into the potential benefits and risk levels of the relevant pricing strategies. However, as often evident in decision making under deep uncertainty, trade-offs between these metrics exist. There are mainly two trade-offs identified in the results which will be further explored in the subsections. First, we will examine the trade-off between profit vs risk. Second, we will examine the trade-off between profitability vs capacity utilisation rate and market share. By analysing these trade-offs, we can identify the strengths and weaknesses of each pricing strategy, which can then form a basis for decision making as we identify the three most relevant pricing policies based on their performance across the different key metrics. Thus, these trade-offs forms insights for answering the second research question was *What pricing strategies of the services will be relevant in this environment*? by further delineating what pricing strategies are relevant from the twelve generated in the optimisation.

5.2.1 Profit vs Risk

The evaluation of performance metrics in the results section show that there seem to be a trade-off between total profit and risk. Where the Dynamic 6 and the Flat/Month pricing policy are in the two different ends of the spectrum of profit, profitability and risk. One interpretation of Figure 5 is that it visualises a classic representation of risk and reward; to be able to increase the total profits, the risk to lose even more is a fact. However, that risk is reflecting the variability *between* scenarios, not *within* them. If a pricing policy would be selected with perfect information about the current scenario, the profits would be much more predictable since then the variability between scenarios would be eliminated. What could be concluded from that is that if a decision maker is well informed about the current scenario, i.e., the current levels of all uncertainties (X) described in this model, it is preferable to choose a policy that is performing well under its best conditions, if those conditions are fulfilled by the current scenario. One such policy is Dynamic 6, that should be aimed for if the market is known to have low demand price elasticity since it performs best of all policies in such conditions. On the contrary, if access to qualitative data about the current environment is scarce it is a safer bet to use a robust policy that is performing well under a larger amount of different positive scenarios but still with a high expected profit, such as Dynamic 4. On the other hand, Dynamic 4 generates the greatest value at risk across negative scenarios of the policies, hence it might be a risky approach for scenarios when the company is non-profitable. A middle way if the scenario is well known when deploying the pricing strategy and it is of high importance to keep variability low and predictability of profit and cash flows high, Flat/month might be a valid choice, as it, for example, is the policy generating the greatest minimum average profit in positive scenarios.

The optimised lever set seen in Appendix C show that Dynamic 6 diverges from the other pricing strategies by it's price-base of market price and market multiplier of 1.2, i.e. a 20% premium on the market's pricing, Dynamic 6 could therefore be considered a premium pricing strategy. As mentioned in the theory section the road freight industry today is characterised by low margins, increased freight costs, and intense competition, thus, today Dynamic 6 might not be a viable approach. But in a future scenario where actors within the industry to a greater extent can differentiate their service or product in terms of, e.g., electrification, digitalisation, environmental impact or general delivery of service this premium pricing strategy entails strong profits.

Similar to Dynamic 6, Dynamic 4 uses a market multiplier but of 1.0 instead of 1.2. This is a low-risk strategy which is flexible to changes in market pricing and attracts customers on equal conditions as the market, i.e. with a 10% margin on costs calculated by the market for every customer contract. The lower risk is due to the fact that it is resistant to demand price elasticity, making it robust to different market conditions. It still maintains a high profitability and total profit compared to the rest of the strategies.

As observed in Figure 5, the performance of the other dynamic pricing strategies is not as remarkable as that of strategies 4 and 6. The clustered placement of Dynamic 1, 2, and 3 signifies that they perform quite well in terms of both profit and risk, without the same profit versus risk trade-off as Dynamic 6. Dynamic 2 and 3 perform slightly better than Dynamic 1, with the primary difference in their lever sets being that these to policies operate on the spot market with a premium for short contracts <=1 month and offer discounts for free capacity. Offering a discounted price on unutilised capacity of trucks in the road freight industry can be considered a case of revenue management. The discounted price would be offered to incentivise customers to use the available capacity and maximise revenue for the business. This strategy can help the business to optimise revenue by filling up the unused capacity with discounted sales, rather than leaving it unused and unprofitable. This suggests that these levers, i.e. taking a premium on spot contracts and offering discounts on free capacity could enhance performance to some extent.

The choice of pricing policy appears to be the most significant factor impacting the performance in terms of total profit, based on the feature scoring in 37, but not equally important for deciding whether a scenario becomes profitable or not, seen in 50. This suggests that the choice of pricing policy is more important for deciding *how* profitable an experiment becomes rather than *if* it becomes profitable or not, forming evidence for focusing more on positive scenarios in the analysis. Even though the pricing policy is the most impactful factor for total profit, the Flat/km policies are performing quite similar to the Dynamic 1-3 pricing strategies in terms of profit and risk, especially the plots for Flat/km 3-5 are very similar, see 5. The Dynamic 1-3 policies, which one could consider being quite similar to the ones being used in the industry today, risk-averse cost-plus pricing, are contrasted by the Flat/km policies which would be a more modern way of pricing. A Flat/km policy is potentially more attractive for customers as proposed in the theory section, for example, procurement professionals generally prefer flat pricing models. Therefore, it might be relevant to test this more modern way of pricing on customers today as the potential loss is seemingly low. Aspects such as an increased customer attraction to e.g. Flat/km was not measured in the model and might therefore be applicable to experiment with on real customers with even better outcomes.

5.2.2 Profitability vs Capacity Utilisation rate and Market Share

Another trade-off in the model output seems to be that a higher profitability is connected to lower capacity utilisation rate and lower market share. When considering Dynamic 6 which has the highest average profitability across all positive scenarios, it is clear that when pricing at a market premium it affects the margins positively at the cost of market share and capacity utilisation rate which is visualised in Figure 36 and Figure 33. Only the customers who are willing to pay more for the service will be attracted to the offer, the ones who are more price-oriented when selecting their service supplier will not be. In an environment with high demand price elasticity, the price-sensitivity is higher and more customers will choose the market's offer. Thus, when letting only premium-payers take part in the service, a large share of the customers will go elsewhere. Further, a pricing strategy, such as Dynamic 6, will let free capacity be left unused if there is not a premium-paying customer ready to pay a premium for the service.

On the other end of the profitability scale, the Flat/Month pricing strategy provides thin but predictable margins on the one hand, but unconquered levels of market share and capacity utilisation rate on the other hand, shown again in Figure 36 and Figure 33. The strategy prices all contracts equally in two different segments, 0.5% and 1% margin depending on the size of the customer contract in kms, with a price calculated as the average cost per customer if the desired market rate of 80% is reached. The results show that the strategy with its low margin and high desired market share, which leads to a low average price per customer, quickly lets the strategy end up with a market share in the ranges around the desired market share in the positive scenarios. Further, with a high market share, trucks and chargers are more likely to be allocated to new contracts which increases the capacity utilisation rate. However, it comes with the cost of low profitability, a very low percentage profitable scenarios and high value at risk.

5.3 Scenario Discovery: Finding Preferable and Unpreferable Conditions for Pricing Policies

The insights related to answering research question 3, *What risks and benefits are associated with the selected pricing strategies, and how can they be effectively managed?*, are based mainly on discovering in which future environments a certain pricing policy would be more effective than another. In that way decision makers can manage the risk and benefits of the relevant pricing policies identified by understanding the present scenario and selecting pricing policy with that in mind. The feature scoring conducted and presented in the results section facilitates the discovery of which future environments are preferable and unpreferable respectively for the pricing policies discussed in the previous section.

As mentioned earlier, Dynamic 6 is heavily impacted by the price sensitivity among the customers on the market. In fact, demand price elasticity seems to be the only major impacting feature both in terms of variability measures for all outcomes, as seen in Figure 43, and in terms of an indicator if an experiment becomes profitable or not, which is visualised in Figure 56 and due to the fact that customers are more likely to select low-price alternatives in a market with high demand price elasticity. However, for Dynamic 4, which is another market price based strategy with lower expected risk and average profit, market profit margin is an impactful uncertainty in terms of both total profit, Figure 41, and if the experiment becomes profitable or not, Figure 54. As the strategy prices at a rate identical to the market, it is not a surprise that the market profit margin, in other words how profitable the market is, is a vital feature for deciding the size of profits in an experiment. However, the same feature is topping the ranking of the feature scoring for *total profit > 0* as well, which suggests that even if all values in the interval for market profit margin are positive, a certain market profitability needs to be in place for the Dynamic 4 strategy to be profitable.

Another interesting insight that becomes extra clear from the feature scoring of Dynamic 4 is the impact of market trend on capacity utilisation rate, which shows that investing in capacity when the market seems to be declining seems to be a bad idea if capacity utilisation rate by itself is a desirable outcome. One yet uncommented feature is the truck's energy efficiency in kWh per km, which seems to be not the largest driver for profit variability for any strategy but a major one for almost all. To explain why this effect is standing out and how that information can be used, 10 is a good start. It shows revenue, variable and system costs for a random scenario where Dynamic 4 is the strategy behind the pricing and by that the revenue. This random scenario is actually extreme, as it is showing a case where the variable costs as a share of total cost is small. With the assumptions from the case company, variable costs are usually by far the largest one of the two cost categories. That implies that uncertainties that are important drivers of variable cost will be important drivers for total cost and by that also profit and profitability. KWh per km is one such uncertainty together with truck kms per month. How many kWhs a truck is using per km is a vital technological efficiency measure which partly is within control of the company. With technological advancements and efficient route-planning the value can be decreased, creating competitive advancements. In terms of risk mitigation, knowing that kWh per km is impactful not only by itself but also together with the electricity price. Together the two uncertainties can create perfect storms in variable cost variability which makes long repricing intervals and flat pricing strategies less desirable.

A less intuitive conclusion from the Dynamic 4 results is that a *low* truck kms per month value is necessary for the strategy to work well. This is due to the fact that truck kms per month is defining the range a truck can drive per month in the urban environment in practice, and therefore indirectly how many trucks are needed to fulfill a customer contract. If that value is low, more trucks are needed, a higher price is set by both the case company and the market on the contract and the fixed cost share of total costs is higher. A higher share of fixed costs implies higher predictability in costs. That in combination with decreasing fixed costs, by efficient route planning, innovation, scale in production or other reasons improves performance in terms of profit and profitability for almost all strategies, specifically of Flat/month which will be discussed below.

The results suggests further that Flat/month performs best when both yearly variable cost change trend and yearly fixed cost change trend are negative, indicating a decreasing trend in variable and fixed costs. This is because a Flat/month pricing strategy provides constant and predictable revenue streams, which makes it an attractive option in an environment where costs are expected to decrease. Costs that are within control of the case company are mainly related to digitalisation, innovation and efficiency. If the company would have access to more qualitative route data, it might be able to streamline the route planning and reduce the number of truck drivers or even trucks, reducing both labour and capacity cost. Another example is the technology shift towards autonomous driving which might also be a contributor to reducing both fixed and variable cost over time which would reward a Flat/month strategy.

Furthermore, the results show that a positive yearly total market demand trend enhances the performance of the Flat/month pricing strategy. This can be attributed to the fact that a positive trend in market demand creates a larger pool of potential customers, making it easier for the case company to maintain a stable customer base and generate reliable revenue streams. In contrast, when either yearly variable cost change trend or yearly fixed cost change trend is positive, the Flat/month pricing strategy is less effective. This is because an increasing trend in costs reduces profit margins and may require more flexible pricing structures to remain competitive. Similarly, when the yearly total market demand trend is negative, the Flat/month pricing strategy may result in reduced revenue due to a smaller pool of potential customers. The results also suggests that a necessary condition for predictable revenues are predictable costs. That is emphasised by the fact that a high variability in contract kms, which is a driver for how many trucks and chargers are being invested in, in the model, causes internal cost variability which is counter-productive for a Flat/month pricing strategy.

5.4 A General Discussion on Innovative Pricing Strategies

As current pricing strategies on the ICET heavy-duty road freight market are based on cost plus methods, it might be interesting to explore when innovative pricing strategies are preferable to use. Using total profit, profitability and share of profitable scenarios as main indicators of a successful outcome is disadvantageous for flat pricing strategies in general and Flat/month in particular as they in this thesis are under-performing alternative policies. However, the Flat/month pricing strategy seems to be especially suitable when the primary aim for the firm is to penetrate the market, maximise utilisation of capacity and keep a steady stream of predictable profit which is in line with previous discussion on trade-offs between profit, market share and utilisation rate. Therefore, depending on the primary aim of the pricing policy, flat strategies have other critical positive outcomes beyond maximising the total profits of the lifespan of the model. Further, not captured by this model, a flat pricing strategy can reduce the internal complexity for pricing functions, offers simpler scaling of the number of customers and may attract customers that appreciates predictability in their own costs.

6
Conclusion and Future Work

The aim of this thesis was to investigate the outcomes of different relevant pricing strategies for electric-only heavy-duty road freight services in a digitalised urban environment. The study used computational EMA models to analyze the effects of different pricing strategies under various conditions in a multitude of scenarios. By evaluating the profit, profitability, risk, market share and other outcomes of each pricing strategy over time, the study aimed to provide decision makers with a basis for decision making with a focus on identifying relevant pricing strategies for electric and digital road freight in an urban environment.

The model created captures the system delineated across a multitude of scenarios for how different aspects, such as technology, market and the cost base might develop in the future. The outcomes have been validated and metrics such as profitability and risk are reasonable in comparison with today's comparable metrics. In terms of research question one, the model created, illustrated by Figure 6, is representing the system in a broad and realistic sense while being flexible for the future development of parameters and internal models. For research question two, the optimization resulting in 12 pricing strategies is shown in Table 5 and the discussion on trade-offs and adaptation of policies in different future conditions highlights the most relevant pricing strategies for the scope of this thesis. Research question three on risks, benefits and how to manage them are in the results section presented and described by the feature scoring and outcome distributions in Appendix E and is discussed in the same sections as for research question two.

The discussion on how different conditions impact the relevance of pricing policies in combination with the discussion on trade-offs show that there does not seem to be a one size fits all pricing policy that is best, which is in line with the theory of deep uncertainty that rather highlights robustness. However, there are some best performing policies from three main perspectives. High risk, high potential profits, secondly the low risk and low potential profits approach, and thirdly, a more moderate approach to the verticals. Here it is evident that Dynamic 6, respectively Flat/Month and Dynamic 4 stands out. The choice of a pricing strategy depends on a business's specific goals, context, and uncertainties. If a decision maker is well-informed about the current scenario and aims to increase total profits, a pricing policy like Dynamic 6 may be suitable. However, if there is limited access to qualitative data, a more robust policy like Dynamic 4, which performs well under a wider range of scenarios, may be preferable. The Flat/month approach could be appropriate for maintaining low variability and high predictability of profit and cash flows in a well-known scenario. The other policies, which also are of relevance, could as discussed also be top-performers in conditions which are outside the frame of the model. For example, Flat/km could be a more modern alternative to today's approach to pricing in the road freight sector. To further analyze this, future research could further explore the relationship between pricing strategies and its impact on consumer behavior, and the overall system performance.

The results of this thesis, we firmly believe, show that computational EMA models can be effectively used as a tool to explore pricing strategies in systems of deep uncertainty. To address the issue of deep uncertainty, it is necessary to explore a multitude of plausible futures. This can be especially relevant for a situation like the future of road freight which is an industry under disruptive change with multiple potential trajectories for many different aspects and variables. The MORO approach employed enables an exploration of these different trajectories by testing the pricing policies across thousands of scenarios.

However, testing the pricing policies across all of these different scenarios creates a paradox since decision makers in the future will know the conditions of that future, thus, many of the scenarios explored and the parameters in such a scenario will be irrelevant in that future. We handled this by assuming that a decision maker would only deploy a policy in an environment where it would work, i.e. be profitable, and chose to look at the subset of scenarios where each policy was profitable when analysing the results, to reduce the extreme variation in profit between very different scenarios. This could certainly be handled differently, by dividing the scenarios into other relevant subsets or by taking this into account before creating the actual model. This also motivates creating a less complex model, taking into account only the "need to have" internal models and parameters, when exploring future scenarios.

In the model created the case company's and the market is highly homogeneous in how the actors price costs, making it challenging to model a future market accurately. This is easier in an existing system with data on how actors currently behave. Additionally, it is important to note that the assumptions and parameters of the model may not be universally applicable, as it is based on case company data, and it may not be able to capture unforeseen changes in the market, government policies, and technological trajectories. Moreover, the study's focus on the Swedish road freight market in an urban area means that the results may not be applicable in other countries with different market conditions, regulations, and consumer behavior. To adjust for these limitations, future studies should develop models customized to the specific case in terms of modeling, data, and assumptions. It is could also be beneficial to incorporate more historical data and trends, such as customer churn rates and market demand trends, to provide more certainty in predicting future trends.

Our thoughts regarding future work could be broken down into the following five areas:

1. Methodology-wise, alternatives to MORO should be investigated. If computational power is not a limitation, we still believe MORO is the best alternative but with more scenarios to optimize on and with a higher number of function evaluations. Otherwise, a good alternative would be to either pre-define a number of pricing policies or scenarios instead of leaving that task entirely to the optimization. The number of lever combinations in the number of scenarios available gives an extremely large number of possible experiments to sample from, which as mentioned is computationally costly to optimize in. Furthermore, there are a huge number of metrics to optimize for as well. In this thesis, robustness across scenarios and high profits were considered dominant as a combination. A single-objective approach as simple directed search on profit would likely have generated higher mean profits, but also higher standard deviations. By discussing with more stakeholders in the sector and finding other possible metrics to optimize for, new interesting policies can be developed.
2. There are certainly a number of effects and causal relationships that were not modelled in this limited time period. Many of them are delimited away by assumptions. We believe that it would be interesting to investigate behavioural mechanisms in deciding on pricing strategies, e.g., simplicity or modern language and branding, and what effect that would have on the customer's sourcing process for a supplier in this sector.
3. The model could with only changing the X and R parts change environment by example looking into Less than Truck Load (LTL) freights or long-haul freights, evaluating the same pricing policies (L) with the same outcomes (M).
4. As this field is new and the environment changing every day, the assumptions of this thesis may already be outdated. By re-framing and re-evaluating the results with new and more narrow assumptions, the model will slowly pivot towards the actual scenario we are approaching. As more data will be available on uncertainties, the results will be clearer, more reliable and adjusted to the real world.
5. A project could certainly use the code from this thesis as backend in a software, making the methodology available for more actors to use with their own assumptions.

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A

Appendix

A.1 XLRM Parameters Data

Table 6: Non-sensitive uncertainty parameters and their value ranges.

Uncertainty	Value Range	Source
Avg Route Planning Efficiency	[0.5, 1.0]	Handley, L.,(2022)[18]
Charger Lifespan SD Share	[0.0, 0.2]	Own assumption
Company Digitalization Level	[1.0, 10.0]	Own assumption
Contract kms SD Share	[0.0, 0.2]	Own assumption
Contract Time Period SD Share	[0.0, 0.2]	Own assumption
Customer Churn Rate Per Year	[0.0, 0.1]	Saravana, K., (2022)[40]
Demand Price Elasticity	[0.1, 10.0]	Schroten, A. et al., (2011)[42]
Initial Interest Rate	[-0.01, 0.1]	Riksbanken, (2022)[38]
Initial Market Share	[0.1, 0.5]	Own assumption
Initial Spot Contract Share	[0.0, 0.4]	Own assumption
Market Digitalization Level	[1.0, 10.0]	Own assumption
Market Profit Margin	[0.01, 0.15]	NYU Stern (2023) [11]
Monthly Electricity Price SD Share	[0.0, 0.02]	SCB, (2022)[41]
Monthly Interest Rate SD Share	[0.0, 0.1]	Riksbanken, (2022)[38]
Monthly Spot Contract Share SD Share	[0.0, 0.02]	Own assumption
Monthly Total Market Demand SD Share	[0.0, 0.02]	Own assumption
Truck Residual Value Share	[0.0, 0.5]	Basma, H., (2021)[5]
Yearly Electricity Price Trend	[-0.05, 0.05]	SCB, (2022)[41]
Yearly Fixed Cost Change Trend	[-0.025, 0.025]	Own assumption
Yearly Interest Rate Trend	[-0.05, 0.05]	Riksbanken, (2022)[38]
Yearly Total Market Demand Trend	[-0.025, 0.025]	Own assumption
Yearly Variable Cost Change Trend	[-0.025, 0.025]	Own assumption

Table 7: Normalized uncertainty parameters and their value ranges.

Uncertainty	Value Range	Source
Battery Cycles Lifespan Avg	[0.0002083, 0.000333]	Internal data
Charger Lifespan Avg	[1.5e-05, 2e-05]	Internal data
Contract Time Period Avg	[2e-06, 6e-06]	Internal data
Cost Per Charging Infrastructure	[0.00583, 0.0125]	Internal data
Initial Electricity Price	[3.33e-08, 3.33e-07]	SCB, (2022)[41]
Initial Monthly Total Market Demand	[0.667, 1.0]	B. Tano (2023)[44]
Insurance Cost Per Year	[0.00167, 0.00417]	Internal data
Kwh Per Km	[8.33e-08, 1.67e-07]	Internal data
Maintenance Cost Per Km	[0.0, 3.33e-07]	Internal data
Maintenance Cost Per Year	[0.00167, 0.00417]	Internal data
Monthly Contract Kms Avg	[0.000833, 0.0025]	Internal data
Monthly Labour Cost	[0.00333, 0.00583]	Internal data
Truck Kms Per Month	[0.0002083, 0.000458]	Internal data
Truck Purchase Cost	[0.25, 0.417]	Internal data

Table 8: Lever parameters and their value ranges.

Lever	Value Range
Company Profit Margin	[0.01, 0.15]
Flat Price Desired Market Share	[0.2, 1.0]
Flat Price Segments	[1.0, 5.0]
Free Capacity Discount Rate	[0.0, 0.5]
Market Price Multiplier	[0.8, 1.2]
No Short Contract Without Free Capacity	[true, false]
Price Base	[cost, market_price]
Pricing Policy	[dynamic, flat_per_km, flat_per_month]
Repricing Frequency	[1.0, 24.0]
Short Contract Premium Rate	[0.0, 0.5]
Short Contract T Limit	[1.0, 40.0]

A.2 XLRM Parameters Definitions

A.2.1 X - Uncertainties

1. **Avg Route Planning Efficiency**
   The share of driven kms per truck that are related to actual contract deliveries in %. Could also be defined as 1 - % deadhead miles (share of miles one

drives with an empty load, either returning to home base or driving to a new destination to pick up a new load).

2. **Charger Lifespan Sd**
   Standard deviation of lifespan in months of a charger.

3. **Company Digitalization Level**
   Decides the uncertainty (standard deviation) of Cost Forecasts and Avg Route Planning Efficiency for the case company.

4. **Contract Kms Sd**
   The standard deviation of the size of a customer contract in tonne-km.

5. **Contract Time Period Sd**
   Standard deviation of a customer contract time period in months.

6. **Customer Churn Rate Per Year**
   Probability of customer terminating contract after yearly repricing (churn rate per year).

7. **Demand Price Elasticity**
   Price-elasticity of demand of urban heavy duty freight services. The percentage change in the quantity demanded of a good or service divided by the percentage change in the price.

8. **Initial Interest Rate**
   Initial interest rate in percentage in Sweden.

9. **Initial Market Share**
   The initial market share of case company.

10. **Initial Spot Contract Share**
    The share of contracts that are sold on the spot market, i.e. only priced for the next month.

11. **Market Cost Based Profit Margin**
    The average profit margin in % of the market.

12. **Market Digitalization Level**
    Decides the uncertainty (standard deviation) of Cost Forecasts and Avg Route Planning Efficiency for the market.

13. **Monthly Electricity Price Sd**
    Standard deviation of electricity price in % in Sweden.

14. **Monthly Interest Rate Sd** Standard deviation of interest rates in % in

Sweden.

15. **Monthly Spot Contract Share Sd**
The standard deviation of the share of contracts that are spot priced in %.

16. **Monthly Total Market Demand Sd**
The standard deviation of monthly total market demand in % in the area of Greater Gothenburg.

17. **Truck Residual Value Share**
The residual value of the truck including the battery as % of the purchase price.

18. **Yearly Electricity Price Trend**
The yearly change trend of electricity prices in Sweden.

19. **Yearly Fixed Cost Change Trend**
The yearly change trend of all parameters in system cost, i.e. truck price and charging infrastructure price.

20. **Yearly Interest Rate Trend**
The change trend of interest rates per year in % in Sweden.

21. **Yearly Total Market Demand Trend**
The yearly trend of total market demand in % in Greater Gothenburg.

22. **Yearly Variable Cost Change Trend**
The yearly change trend of parameters in variable contract cost except electricity price, i.e. maintenance cost and labour cost.

23. **Battery Cycles Lifespan Avg**
The average lifespan in number of cycles, i.e. a full discharge and recharge of the battery used in the type of truck, with a certain battery size used for heavy-duty urban transports. Also assuming an 80% total maximum discharge of battery capacity.

24. **Charger Lifespan Avg**
Average lifespan in months of a 30 kW depot charger.

25. **Contract Time Period Avg**
The average length in months of a case company customer contract for heavy-duty urban transports.

26. **Cost Per Charging Infrastructure**
The total deployment cost per charger in SEK. 30 kW DC charger incl. investment cost, installation, ground work, cables.

27. **Initial Electricity Price**
    Initial electricity price in SEK/kWh in region.

28. **Initial Monthly Total Market Demand**
    The monthly total market demand in km in the area of Greater Gothenburg.

29. **Insurance Cost Per Year**
    The insurance cost of an urban rigid truck in SEK/yr.

30. **Kwh Per Km**
    The kWh of energy consumption per km driven.

31. **Maintenance Cost Per Km**
    Maintenance cost in SEK/km.

32. **Maintenance Cost Per Year**
    The cost of maintainance for an urban rigid truck in SEK/yr. There is both a maintenance cost per year and one depending on km driven.

33. **Monthly Contract Kms Avg**
    The average size in kms of a case company customer contract for FTL heavy-duty urban transports.

34. **Monthly Labour Cost**
    The monthly labour cost for daytime operations in SEK.

35. **Truck Kms Per Month**
    The number of kilometers driven per operative heavy-duty urban truck during a month.
36. **Truck Purchase Cost**
    The purchase cost of a heavy-duty urban rigid truck including battery in SEK.

A.2.2 L - Levers

1. **Company Profit Margin**
   Decides which profit margin in % as a markup on the cost forecast that will be set for all customer proposals in ther RFQ model.

2. **Flat Price Desired Market Share**
   Decides a market share that the company wants to take which then influences the flat pricing to ensure the desired market share is acheived.

3. **Flat Price Segments**
   This is a tiered flat pricing strategy where the pricing towards customers are segmentated in up to 5 different customer segments. The pricing for the specific segments are based on intervals of the contract sizes in monthly kms.

Generating a discounted price /km or /month for the segments with greater km intervals.

4. **Free Capacity Discount Rate**
Sets a discount rate for customer contracts when there is available truck and charger capacity to fulfill the contract, in order to maintain a high utilization rate of hardware.

5. **Market Price Multiplier**
The multiplier used to base the company pricing on the market rate, only used if price base is market price. Could be both below or above the market rate.

6. **No Short Contract Without Free Capacity**
A binary model that is either True or False. If true, then the company won't accept any short contracts on the spot market, how long the market is is decided by Lever 11 "Short Contract T Limit).

7. **Price Base**
The price can either be based on costs or the market price.

8. **Pricing Policy**
Decides whether to apply one of three pricing policies: dynamic, flat rate per km, flat rate per month. If the pricing policy is *flat/km or flat/month*, the pricing model estimates the total system and variable costs to needed take the desired market share, then distributes it per km or per month for all potential future customer contracts and then adds the margin. If the pricing policy is *dynamic*, the company pricing model calculates a suggested monthly contract price based on the fixed system costs and the variable/km costs for the specific contract and then adding potential levers which results in the price.

9. **Repricing Frequency**
The frequency in months at which the price is recalculated based on the new current market price or forecasted cost base.

10. **Short Contract Premium Rate**
The premium rate added on the price for accepting short contracts at the spot market.

11. **Short Contract T Limit**
Decides whether a contract is defined as short or long based on length in months.

A.2.3 R - Internal Models

1. **Company Pricing Model**
   This model takes in various parameters related to a contract and produces a suggested price for that contract. It determines the pricing policy to apply, with options for a flat per-km rate, a flat per-month rate, or a dynamic rate based on either cost or market price. The function then adjusts the suggested price based on various factors, including forecast factors, contract length, and available capacity, before returning the final suggested price for the contract.

2. **Contracted Additional Capacity Model**
   Calculates the additional capacity needed to take on another contract that has been accepted.

3. **Contract Acceptance Model**
   This model is used to determine the probability of a customer accepting a contract based on various factors. It takes in contract parameters, including the suggested market price and demand price elasticity. The function then calculates the probability of acceptance based on the contract price compared to the market price and the standard deviation of the distribution.

4. **Electricity Price Model**
   The electricity price model takes in parameters related to electricity pricing and produces a predicted electricity price for the current month. It uses a normal distribution to generate a variable for the current month's electricity price based on the mean electricity price, standard deviation, and a change trend for electricity prices over time.

5. **Interest Rate Model**
   This model generates the interest rate based on its mean, standard deviation, and change trend over time.

6. **Market Demand Model**
   This model generates the monthly market demand at time step t for heavy-duty road freight services in the Greater Gothenburg area. It produces this prediction for the total market demand in the future based on the current market demand, standard deviation and yearly change trend over time.

7. **Market Pricing Model**
   The market pricing model calculates the markets pricing of heavy-duty road freight services based on the forecasted system costs and variable contract costs and then adds the market's desired margin. This is then the suggested price from the market.

8. **Parameter Forecasting Model**
   In this model the forecasting capability is influenced by the digitalization level of company or market i.e. the standard deviation of forecast. If the digitaliza-

tion level of the company is high it is assumed to have better data to enable improved predictions.

9. **Replacement Model**
   Calculates the replacement of hardware needed at time step t due to battery or charging infrastructure lifelength overdue.

10. **Repricing Model**
    In this model, the repricing of customer contracts are generated. It is a probabilistic function where the customer accepting the contract or not is depending on the churn rate, suggested market contract price and demand price elasticity.

11. **RFQ Model**
    The RFQ model simulates an unsupplied market demand for trucks. The function generates proposals for customer contracts to fulfill this demand, where the amount of demand being fulfilled using spot contracts and non-spot contracts is calculated based on the current share of spot contracts. For each contract, it generates a contract length and the contract start and end times, the contract length in kilometers, and the number of trucks needed per kilometer for the contract.

12. **Spot Contract Share Model**
    This is a probabilistic model that generates the spot contract share at time step t as a number from normal distribution.

13. **System Cost Model**
    To determine the total fixed system cost per time step t (month), add the cost of truck purchase (including the battery) per month to the charging infrastructure cost per month. The lifetime costs of both the truck and charger are divided by their respective lifespans to arrive at the monthly cost.

14. **Trucks Needed Per Contract Km Model**
    Takes the Avg Route Planning Efficiency, Digitalization Level and Truck Kms Per Month to calculate the number of trucks needed per km operated in a customer contract.

15. **Variable Contract Cost Model**
    Calculates the total variable contract cost per km by adding maintenance cost/km, labour cost/km and electricity cost/km.

A.2.4 M - Outcomes

1. **Actual Revenue**
   The actual total revenue generated at time step t.

2. **Actual System Cost**

The actual total system costs generated at time step t.

3. **Actual Variable Cost**
   The actual total variable contract costs generated at time step t.

4. **Avg Profit Per Km**
   The average profit generated per km at time step t.

5. **Capacity Utilization Rate**
   The capacity utilization rate, which is the , in percentage, of trucks and chargers that are operational in customer contracts at time step t.

6. **Market Share**
   The market share of the case company at time step t.

7. **Share Profitable Contracts**
   The share of all customer contracts that are profitable.

8. **Share Profitable Months**
   The share of time steps (months) that have been profitable throughout the 240 months/time steps analysed.

9. **Total Profit**
   The actual total profit generated at time step t.

B

Appendix

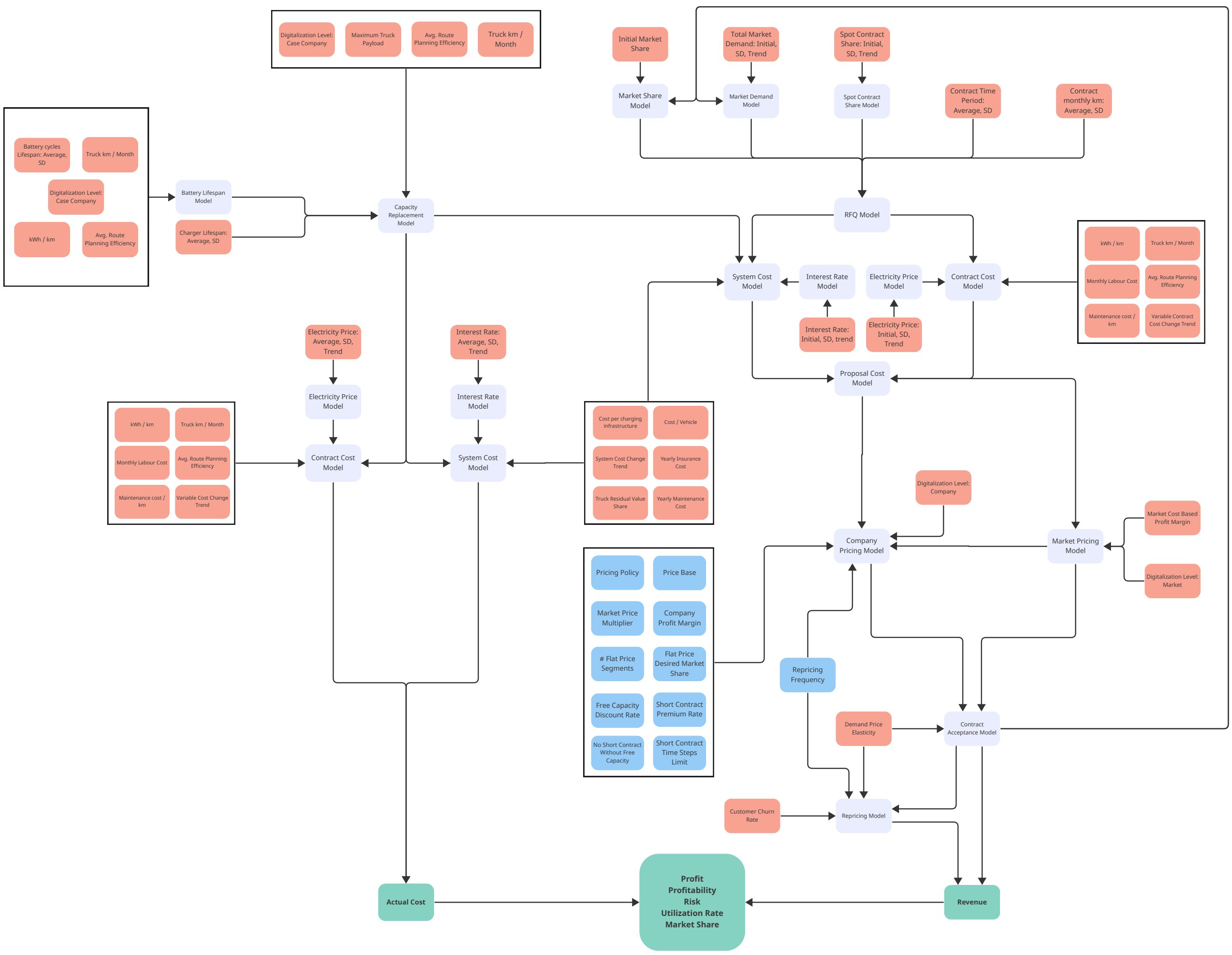

Figure 6: Conceptual model of the system in which the analysis will be performed according to the X (red), L (blue), R (grey) & M (green) framework.

C

Appendix

C.1 Robust Optimization and Exploration Results

Table 9: Optimized lever set for pricing policy: Dynamic 1

Lever	Optimization value
Company Profit Margin	11.25%
Flat Price Desired Market Share	N/A
Flat Price #Segments	N/A
Free Capacity Discount Rate	0
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	False
Price Base	Cost
Pricing Policy	Dynamic
Repricing Frequency	1 (Monthly)
Short Contract Premium Rate	0
Short Contract Time Limit	N/A

Table 10: Exploration results for pricing policy: Dynamic 1

Outcomes/Metrics	Exploration value
Total Profit Mean	50.12
Percentage Profitable Scenarios	61.30 %
Negative Scenarios Profit Mean	-160.79
Negative Scenarios Avg Profitability	-11.07%
Positive Scenarios Profit Mean	183.28
Positive Scenarios Standard Deviation Share of Mean	85.56%
Positive Scenarios Avg Profitability	4.86%
Positive Scenarios Min Avg Profitability	-3.80%
Positive Scenarios Max Avg Profitability	14.21%
Positive Scenarios Share Profitable Contracts	77.52%
Positive Scenarios Average Market Share	48.99%
Positive Scenarios Average Capacity Utilization Rate	93.50%

Table 11: Optimized lever set for pricing policy: Dynamic 2

Lever	Optimization value
Company Profit Margin	15%
Flat Price Desired Market Share	N/A
Flat Price #Segments	N/A
Free Capacity Discount Rate	25%
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	False
Price Base	Cost
Pricing Policy	Dynamic
Repricing Frequency	6 (Bi-annual)
Short Contract Premium Rate	50%
Short Contract Time Limit	1 Month

Table 12: Exploration results for pricing policy: Dynamic 2

Outcomes/Metrics	Exploration value
Total Profit Mean	108.14
Percentage Profitable Scenarios	68.30 %
Negative Scenarios Profit Mean	-101.75
Negative Scenarios Avg Profitability	-12.84%
Positive Scenarios Profit Mean	205.41
Positive Scenarios Standard Deviation Share of Mean	85.67%
Positive Scenarios Avg Profitability	6.59%
Positive Scenarios Min Avg Profitability	-10.60%
Positive Scenarios Max Avg Profitability	16.41%
Positive Scenarios Share Profitable Contracts	80.86%
Positive Scenarios Average Market Share	38.27%
Positive Scenarios Average Capacity Utilization Rate	92.09%

Table 13: Optimized lever set for pricing policy: Dynamic 3

Lever	Optimization value
Company Profit Margin	15%
Flat Price Desired Market Share	N/A
Flat Price #Segments	N/A
Free Capacity Discount Rate	37.5%
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	True
Price Base	Cost
Pricing Policy	Dynamic
Repricing Frequency	12 (Annual)
Short Contract Premium Rate	50%
Short Contract Time Limit	1 Month

Table 14: Exploration results for pricing policy: Dynamic 3

Outcomes/Metrics	Exploration value
Total Profit Mean	107.55
Percentage Profitable Scenarios	68.70 %
Negative Scenarios Profit Mean	-105.09
Negative Scenarios Avg Profitability	-11.12%
Positive Scenarios Profit Mean	204.13
Positive Scenarios Standard Deviation Share of Mean	86.23%
Positive Scenarios Avg Profitability	6.65%
Positive Scenarios Min Avg Profitability	-4.63%
Positive Scenarios Max Avg Profitability	16.15%
Positive Scenarios Share Profitable Contracts	80.79%
Positive Scenarios Average Market Share	37.97%
Positive Scenarios Average Capacity Utilization Rate	92.11%

Table 15: Optimized lever set for pricing policy: Dynamic 4

Lever	**Optimization value**
Company Profit Margin	11.5%
Flat Price Desired Market Share	N/A
Flat Price #Segments	N/A
Free Capacity Discount Rate	25%
Market Price Multiplier	1.0
No Short Contract Without Free Capacity	False
Price Base	Market Price
Pricing Policy	Dynamic
Repricing Frequency	6 (Bi-annual)
Short Contract Premium Rate	50%
Short Contract Time Limit	20 Months

Table 16: Exploration results for pricing policy: Dynamic 4

Outcomes/Metrics	**Exploration value**
Total Profit Mean	39.71
Percentage Profitable Scenarios	58.50%
Negative Scenarios Profit Mean	-218.62
Negative Scenarios Avg Profitability	-7.22%
Positive Scenarios Profit Mean	222.97
Positive Scenarios Standard Deviation Share of Mean	82.30%
Positive Scenarios Avg Profitability	5.92%
Positive Scenarios Min Avg Profitability	-5.45%
Positive Scenarios Max Avg Profitability	16.64%
Positive Scenarios Share Profitable Contracts	81.19%
Positive Scenarios Average Market Share	50.63%
Positive Scenarios Average Capacity Utilization Rate	94.63%

Table 17: Optimized lever set for pricing policy: Dynamic 5

Lever	Optimization value
Company Profit Margin	11.5%
Flat Price Desired Market Share	N/A
Flat Price #Segments	N/A
Free Capacity Discount Rate	50%
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	False
Price Base	Cost
Pricing Policy	Dynamic
Repricing Frequency	1 (Monthly)
Short Contract Premium Rate	12.5%
Short Contract Time Limit	20 Months

Table 18: Exploration results for pricing policy: Dynamic 5

Outcomes/Metrics	Exploration value
Total Profit Mean	73.85
Percentage Profitable Scenarios	59.10%
Negative Scenarios Profit Mean	-119.15
Negative Scenarios Avg Profitability	-18.65%
Positive Scenarios Profit Mean	204.60
Positive Scenarios Standard Deviation Share of Mean	85.67%
Positive Scenarios Avg Profitability	6.59%
Positive Scenarios Min Avg Profitability	-10.60%
Positive Scenarios Max Avg Profitability	16.41%
Positive Scenarios Share Profitable Contracts	80.86%
Positive Scenarios Average Market Share	38.27%
Positive Scenarios Average Capacity Utilization Rate	92.09%

Table 19: Optimized lever set for pricing policy: Dynamic 6

Lever	Optimization value
Company Profit Margin	11.5%
Flat Price Desired Market Share	N/A
Flat Price #Segments	N/A
Free Capacity Discount Rate	25%
Market Price Multiplier	1.2
No Short Contract Without Free Capacity	False
Price Base	Market Price
Pricing Policy	Dynamic
Repricing Frequency	6 (Bi-Annual)
Short Contract Premium Rate	0%
Short Contract Time Limit	20 Months

Table 20: Exploration results for pricing policy: Dynamic 6

Outcomes/Metrics	Exploration value
Total Profit Mean	158.16
Percentage Profitable Scenarios	49.30%
Negative Scenarios Profit Mean	-8.99
Negative Scenarios Avg Profitability	-10.36%
Positive Scenarios Profit Mean	323.49
Positive Scenarios Standard Deviation Share of Mean	125.00%
Positive Scenarios Avg Profitability	13.03%
Positive Scenarios Min Avg Profitability	-27.22%
Positive Scenarios Max Avg Profitability	30.77%
Positive Scenarios Share Profitable Contracts	85.42%
Positive Scenarios Average Market Share	22.83%
Positive Scenarios Average Capacity Utilization Rate	83.86%

Table 21: Optimized lever set for pricing policy: Flat/km 1

Lever	Optimization value
Company Profit Margin	15%
Flat Price Desired Market Share	60%
Flat Price #Segments	3
Free Capacity Discount Rate	N/A
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	N/A
Price Base	N/A
Pricing Policy	Flat Per Km
Repricing Frequency	12 (Annual)
Short Contract Premium Rate	N/A
Short Contract Time Limit	N/A

Table 22: Exploration results for pricing policy: Flat/km 1

Outcomes/Metrics	Exploration value
Total Profit Mean	-40.54
Percentage Profitable Scenarios	52.00%
Negative Scenarios Profit Mean	-269.44
Negative Scenarios Avg Profitability	-9.01%
Positive Scenarios Profit Mean	170.75
Positive Scenarios Standard Deviation Share of Mean	92.07%
Positive Scenarios Avg Profitability	4.36%
Positive Scenarios Min Avg Profitability	-1.99%
Positive Scenarios Max Avg Profitability	13.55%
Positive Scenarios Share Profitable Contracts	77.15%
Positive Scenarios Average Market Share	53.22%
Positive Scenarios Average Capacity Utilization Rate	93.81%

Table 23: Optimized lever set for pricing policy: Flat/km 2

Lever	**Optimization value**
Company Profit Margin	11.5%
Flat Price Desired Market Share	40%
Flat Price #Segments	1
Free Capacity Discount Rate	N/A
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	N/A
Price Base	N/A
Pricing Policy	Flat Per Km
Repricing Frequency	1 (Monthly)
Short Contract Premium Rate	N/A
Short Contract Time Limit	N/A

Table 24: Exploration results for pricing policy: Flat/km 2

Outcomes/Metrics	**Exploration value**
Total Profit Mean	-60.13
Percentage Profitable Scenarios	49.50%
Negative Scenarios Profit Mean	-286.02
Negative Scenarios Avg Profitability	-10.53%
Positive Scenarios Profit Mean	170.32
Positive Scenarios Standard Deviation Share of Mean	92.07%
Positive Scenarios Avg Profitability	4.25%
Positive Scenarios Min Avg Profitability	-2.02%
Positive Scenarios Max Avg Profitability	12.43%
Positive Scenarios Share Profitable Contracts	77.46%
Positive Scenarios Average Market Share	54.16%
Positive Scenarios Average Capacity Utilization Rate	93.72%

Table 25: Optimized lever set for pricing policy: Flat/km 3

Lever	Optimization value
Company Profit Margin	15%
Flat Price Desired Market Share	100%
Flat Price #Segments	1
Free Capacity Discount Rate	N/A
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	N/A
Price Base	N/A
Pricing Policy	Flat Per Km
Repricing Frequency	Every 18 Months
Short Contract Premium Rate	N/A
Short Contract Time Limit	N/A

Table 26: Exploration results for pricing policy: Flat/km 3

Outcomes/Metrics	Exploration value
Total Profit Mean	34.40
Percentage Profitable Scenarios	61.90%
Negative Scenarios Profit Mean	-229.61
Negative Scenarios Avg Profitability	-11.23%
Positive Scenarios Profit Mean	196.53
Positive Scenarios Standard Deviation Share of Mean	90.69%
Positive Scenarios Avg Profitability	5.66%
Positive Scenarios Min Avg Profitability	-4.98%
Positive Scenarios Max Avg Profitability	15.24%
Positive Scenarios Share Profitable Contracts	79.70%
Positive Scenarios Average Market Share	45.13%
Positive Scenarios Average Capacity Utilization Rate	92.55%

Table 27: Optimized lever set for pricing policy: Flat/km 4

Lever	Optimization value
Company Profit Margin	15%
Flat Price Desired Market Share	40%
Flat Price #Segments	1
Free Capacity Discount Rate	N/A
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	N/A
Price Base	N/A
Pricing Policy	Flat Per Km
Repricing Frequency	Every 24 Months
Short Contract Premium Rate	N/A
Short Contract Time Limit	N/A

Table 28: Exploration results for pricing policy: Flat/km 4

Outcomes/Metrics	Exploration value
Total Profit Mean	30.65
Percentage Profitable Scenarios	59.70%
Negative Scenarios Profit Mean	-217.63
Negative Scenarios Avg Profitability	-10.43%
Positive Scenarios Profit Mean	197.88
Positive Scenarios Standard Deviation Share of Mean	89.14%
Positive Scenarios Avg Profitability	5.85%
Positive Scenarios Min Avg Profitability	-3.67%
Positive Scenarios Max Avg Profitability	15.71%
Positive Scenarios Share Profitable Contracts	80.16%
Positive Scenarios Average Market Share	44.69%
Positive Scenarios Average Capacity Utilization Rate	92.67%

Table 29: Optimized lever set for pricing policy: Flat/km 5

Lever	Optimization value
Company Profit Margin	15%
Flat Price Desired Market Share	20%
Flat Price #Segments	1
Free Capacity Discount Rate	N/A
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	N/A
Price Base	N/A
Pricing Policy	Flat Per Km
Repricing Frequency	Every 24 Months
Short Contract Premium Rate	N/A
Short Contract Time Limit	N/A

Table 30: Exploration results for pricing policy: Flat/km 5

Outcomes/Metrics	Exploration value
Total Profit Mean	26.58
Percentage Profitable Scenarios	62.00%
Negative Scenarios Profit Mean	-244.20
Negative Scenarios Avg Profitability	-11.88%
Positive Scenarios Profit Mean	192.53
Positive Scenarios Standard Deviation Share of Mean	91.70%
Positive Scenarios Avg Profitability	5.64%
Positive Scenarios Min Avg Profitability	-4.62%
Positive Scenarios Max Avg Profitability	16.07%
Positive Scenarios Share Profitable Contracts	79.59%
Positive Scenarios Average Market Share	44.48%
Positive Scenarios Average Capacity Utilization Rate	92.40%

Table 31: Optimized lever set for pricing policy: Flat/Month

Lever	Optimization value
Company Profit Margin	1%
Flat Price Desired Market Share	80%
Flat Price #Segments	2
Free Capacity Discount Rate	N/A
Market Price Multiplier	N/A
No Short Contract Without Free Capacity	N/A
Price Base	N/A
Pricing Policy	Flat Per Month
Repricing Frequency	6 (Bi-Annual)
Short Contract Premium Rate	N/A
Short Contract Time Limit	N/A

Table 32: Exploration results for pricing policy: Flat/Month

Outcomes/Metrics	Exploration value
Total Profit Mean	-562.74
Percentage Profitable Scenarios	2.60%
Negative Scenarios Profit Mean	-579.30
Negative Scenarios Avg Profitability	-13.70%
Positive Scenarios Profit Mean	57.96
Positive Scenarios Standard Deviation Share of Mean	71.90%
Positive Scenarios Avg Profitability	1.14%
Positive Scenarios Min Avg Profitability	-0.04%
Positive Scenarios Max Avg Profitability	4.34%
Positive Scenarios Share Profitable Contracts	59.45%
Positive Scenarios Average Market Share	76.91%
Positive Scenarios Average Capacity Utilization Rate	97.49%

D

Appendix

D.1 Random Scenario Revenue and Costs

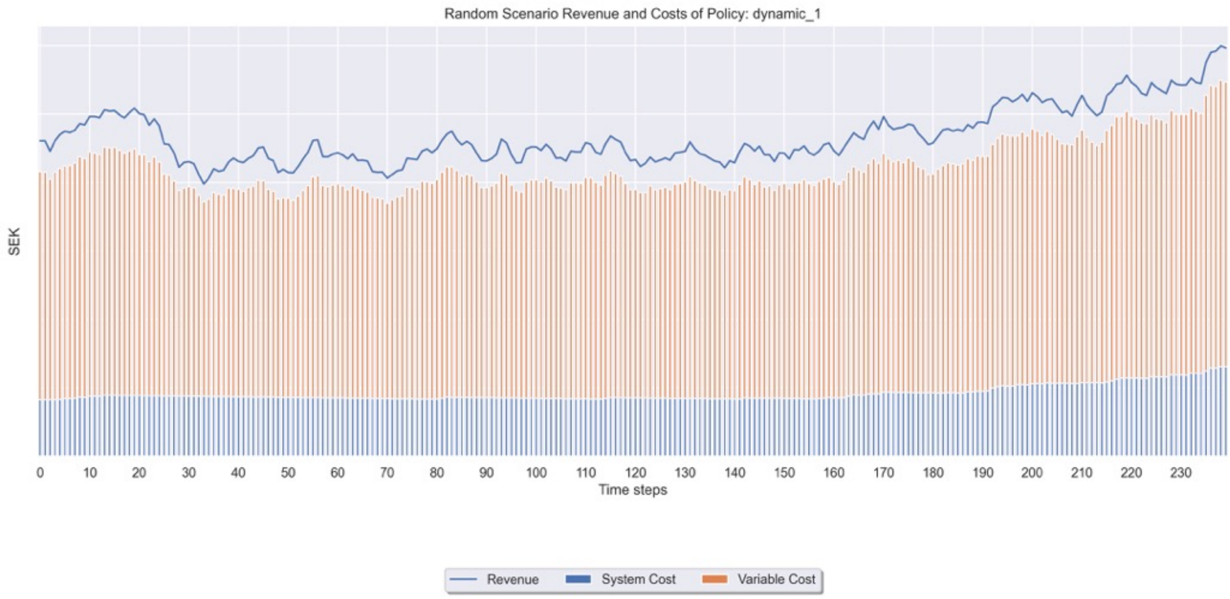

Figure 7: A random scenario showing the total revenue and costs of the pricing policy *Dynamic 1* over 240 months.

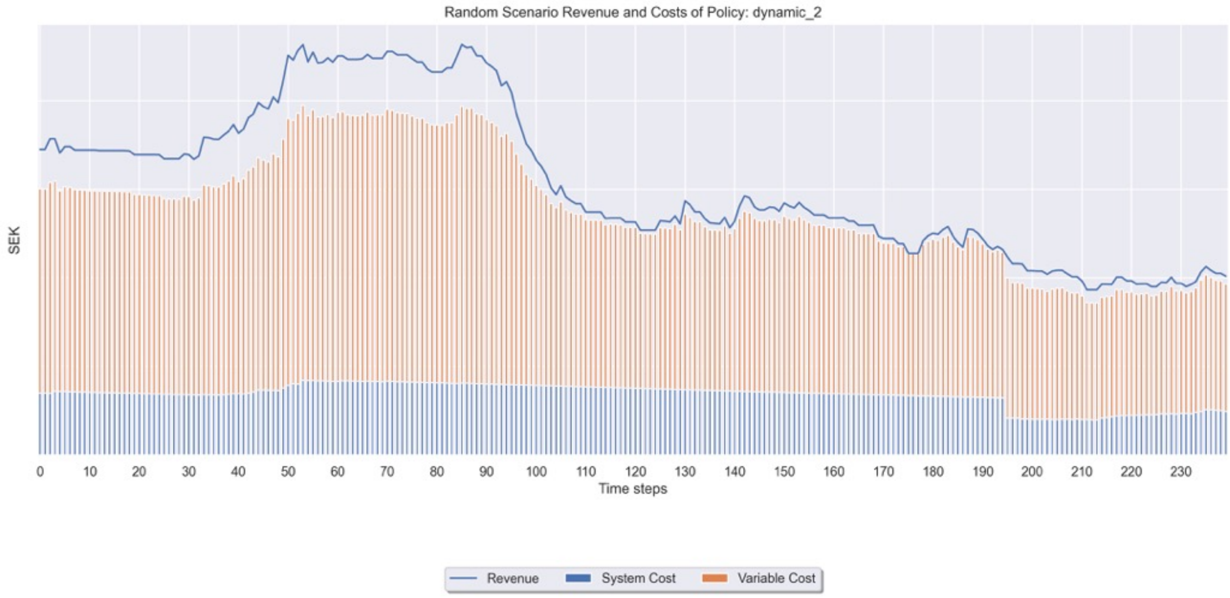

Figure 8: A random scenario showing the total revenue and costs of the pricing policy *Dynamic 2* over 240 months.

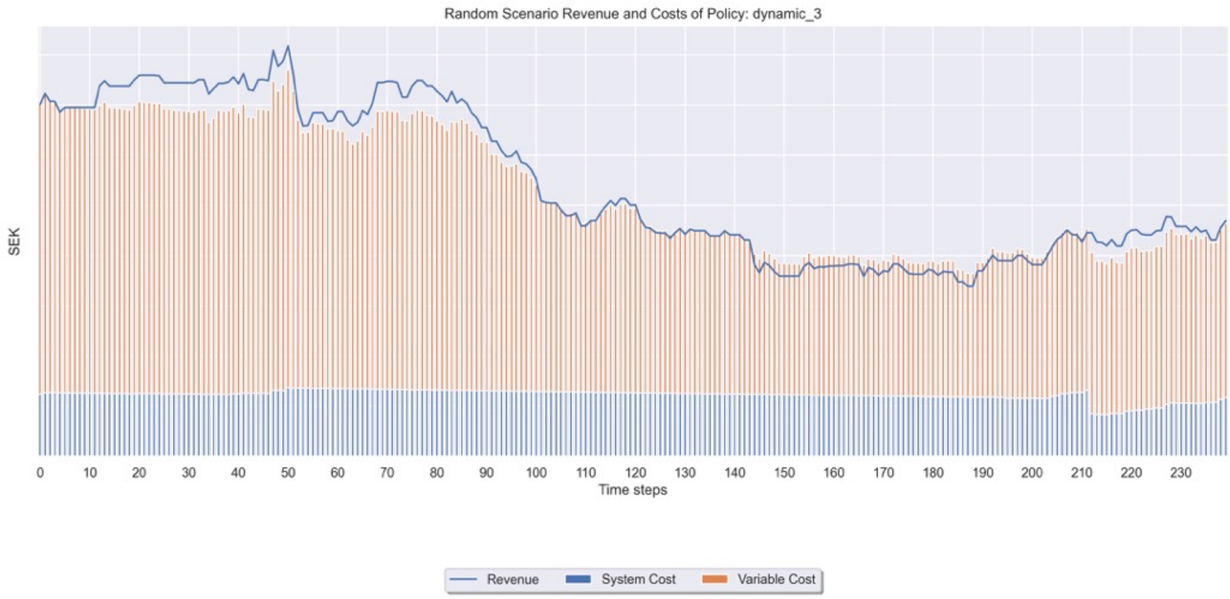

Figure 9: A random scenario showing the total revenue and costs of the pricing policy *Dynamic 3* over 240 months.

Figure 10: A random scenario showing the total revenue and costs of the pricing policy *Dynamic 4* over 240 months.

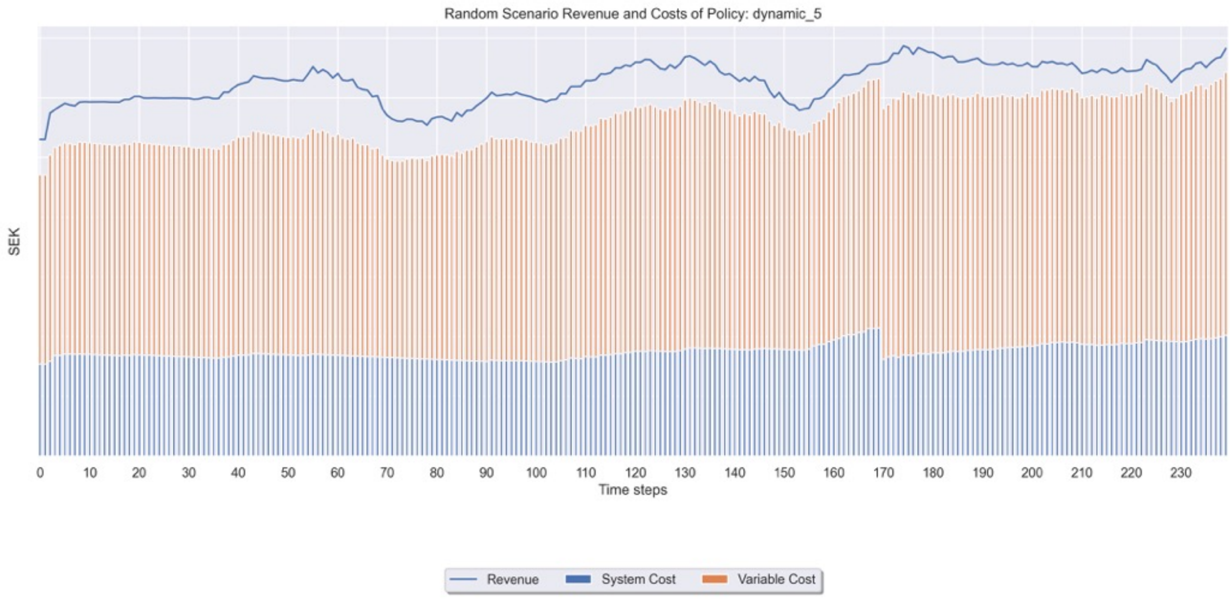

Figure 11: A random scenario showing the total revenue and costs of the pricing policy *Dynamic 5* over 240 months.

Figure 12: A random scenario showing the total revenue and costs of the pricing policy *Dynamic 6* over 240 months.

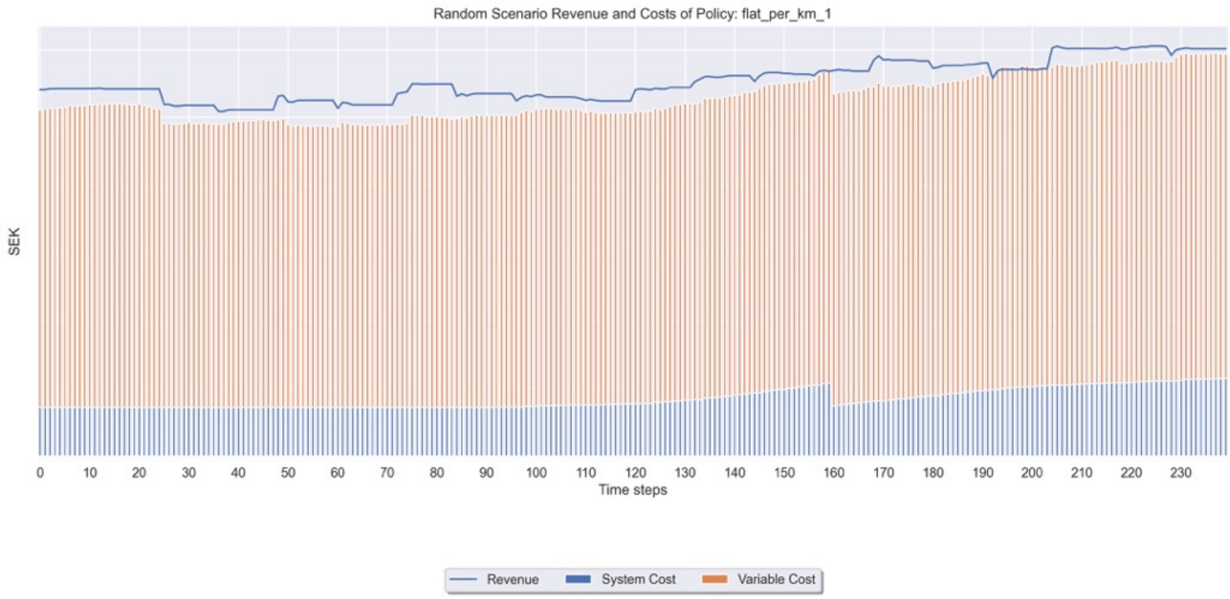

Figure 13: A random scenario showing the total revenue and costs of the pricing policy *Flat Per Km 1* over 240 months.

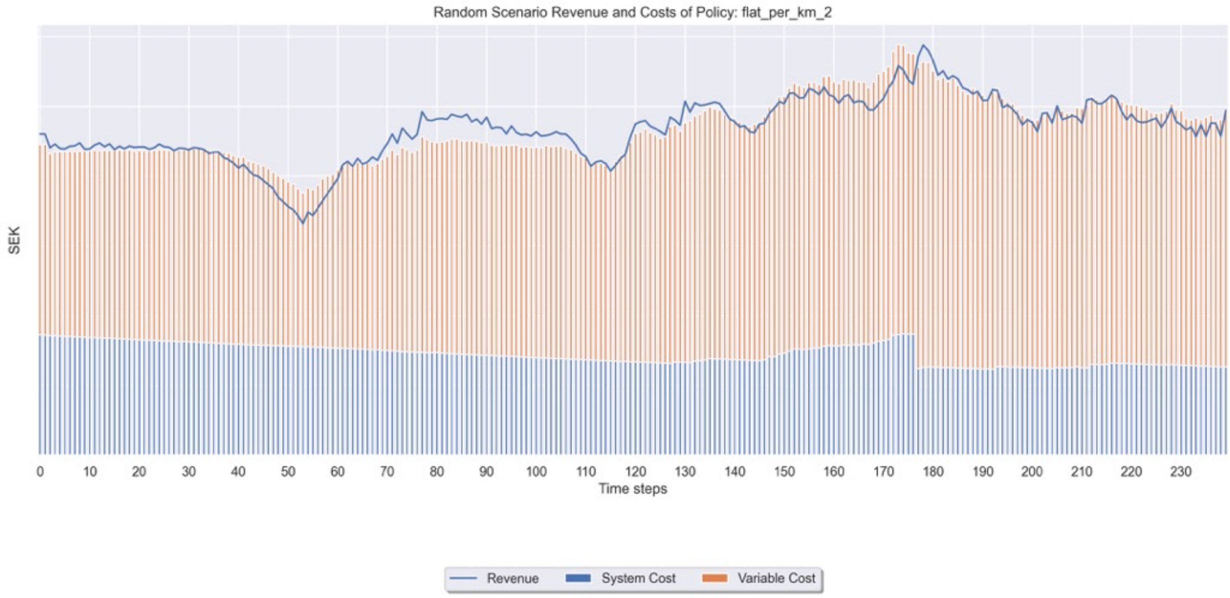

Figure 14: A random scenario showing the total revenue and costs of the pricing policy *Flat Per Km 2* over 240 months.

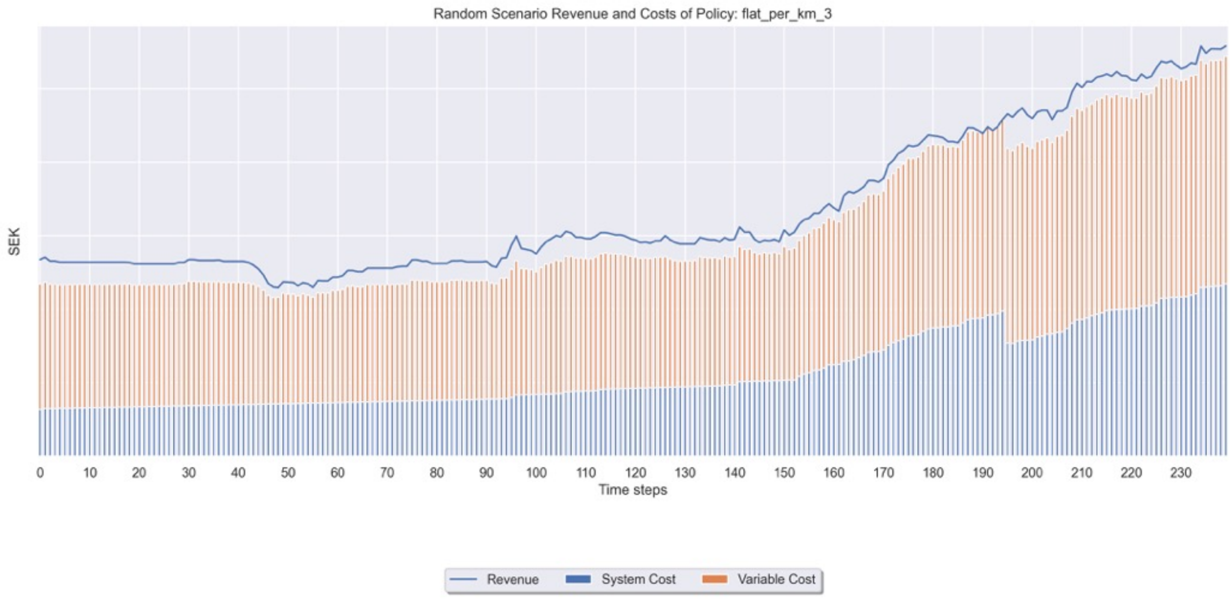

Figure 15: A random scenario showing the total revenue and costs of the pricing policy *Flat Per Km 3* over 240 months.

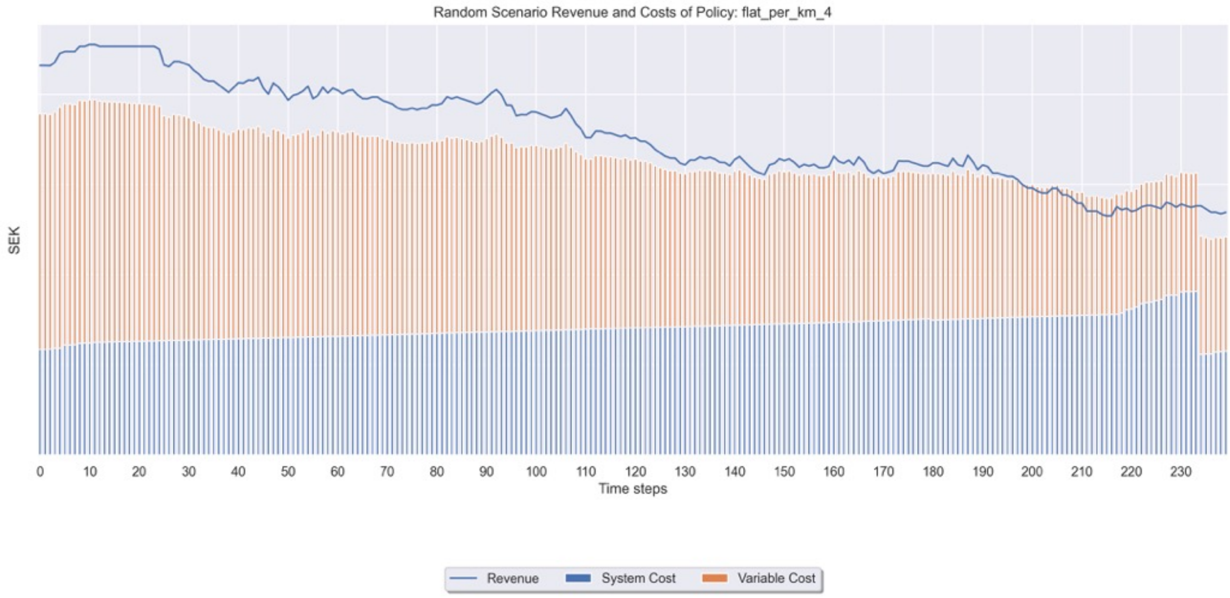

Figure 16: A random scenario showing the total revenue and costs of the pricing policy *Flat Per Km 4* over 240 months.

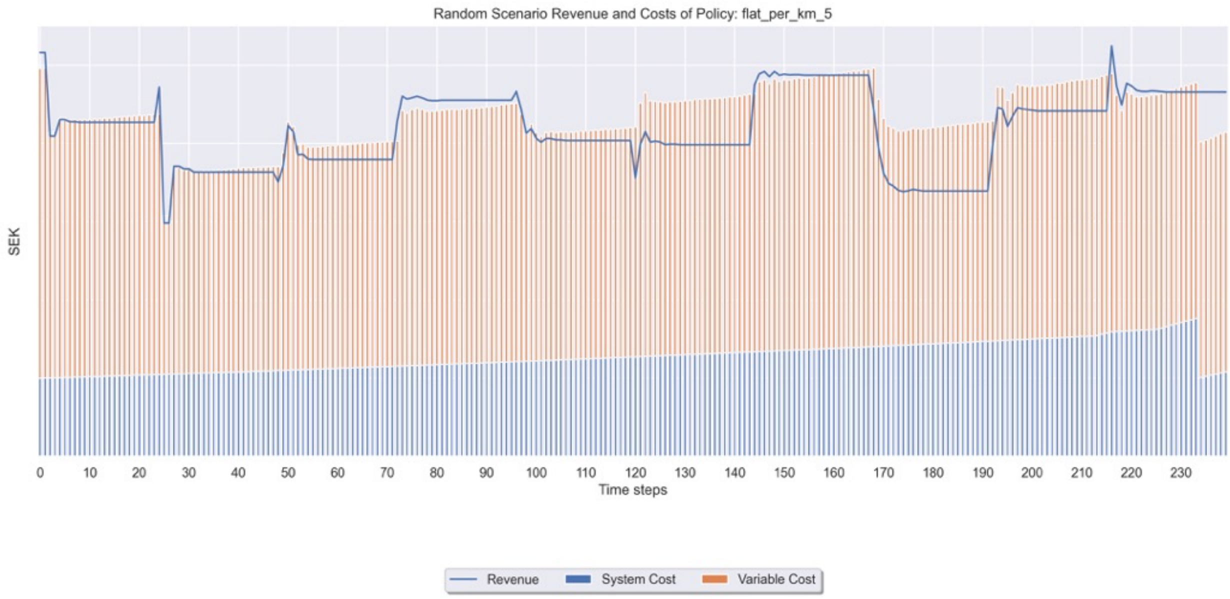

Figure 17: A random scenario showing the total revenue and costs of the pricing policy *Flat Per Km 5* over 240 months.

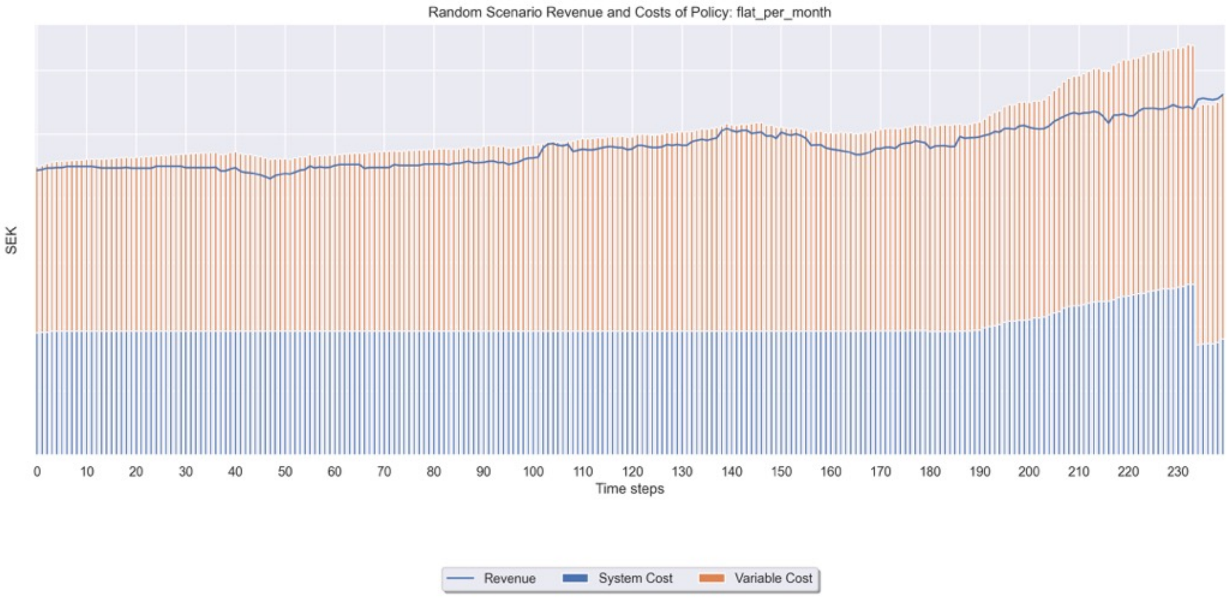

Figure 18: A random scenario showing the total revenue and costs of the pricing policy *Flat Per Month* over 240 months.

D.2 Random Scenario Revenue and Costs Per Contract

Figure 19: A random scenario showing the total revenue and costs per contract of the pricing policy *Dynamic 1* over 240 months.

Figure 20: A random scenario showing the total revenue and costs per contract of the pricing policy *Dynamic 2* over 240 months.

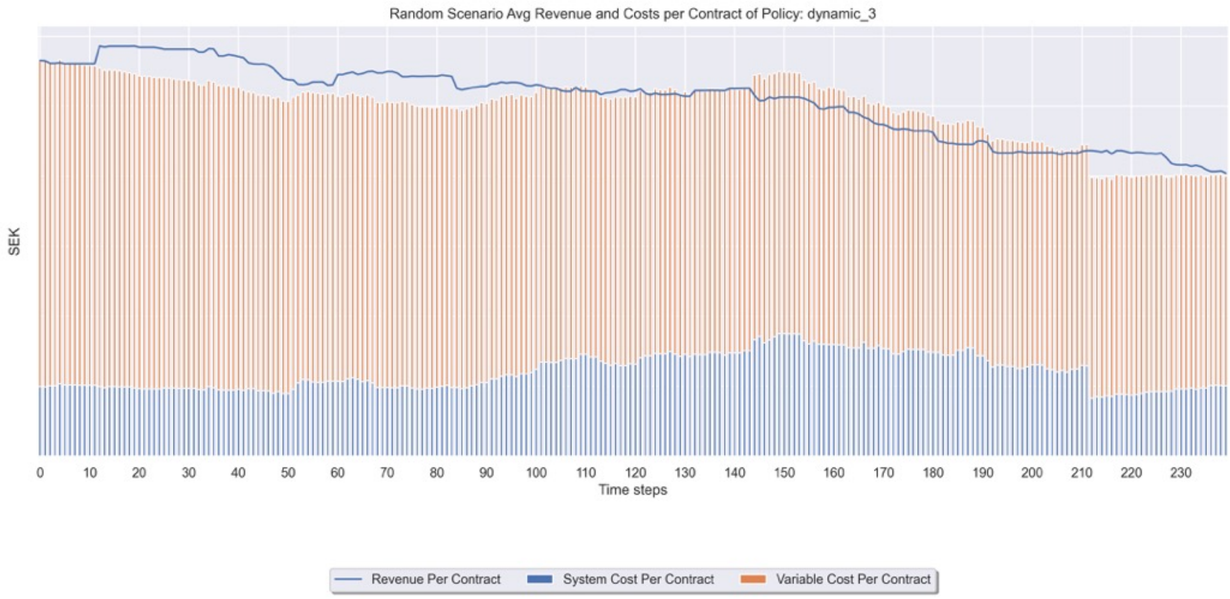

Figure 21: A random scenario showing the total revenue and costs per contract of the pricing policy *Dynamic 3* over 240 months.

Figure 22: A random scenario showing the total revenue and costs per contract of the pricing policy *Dynamic 4* over 240 months.

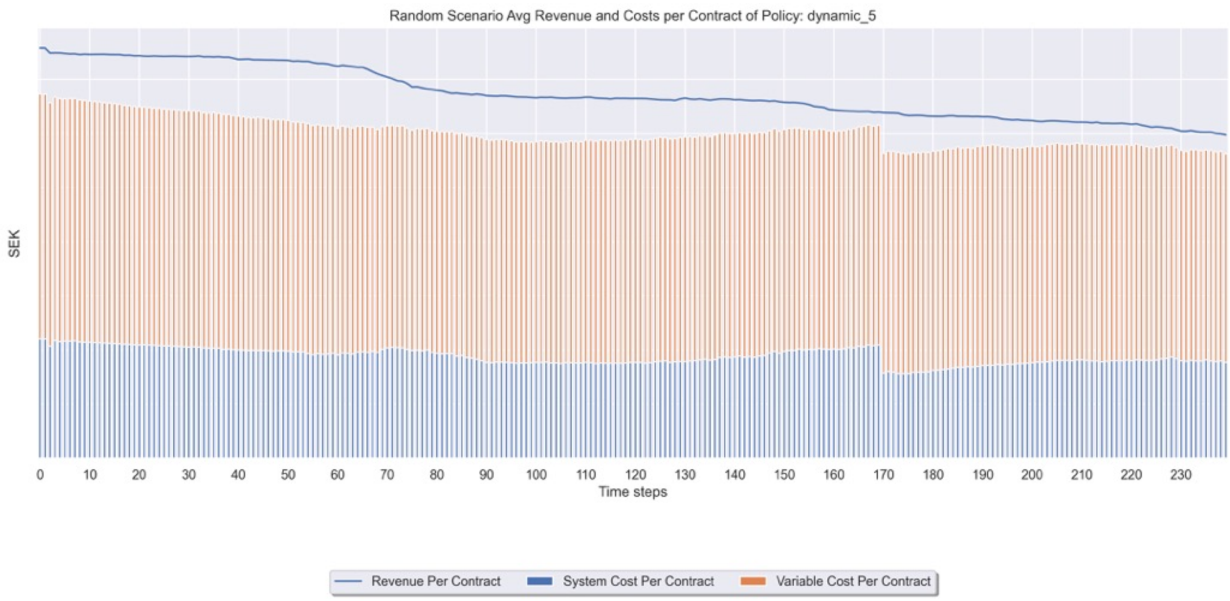

Figure 23: A random scenario showing the total revenue and costs per contract of the pricing policy *Dynamic 5* over 240 months.

Figure 24: A random scenario showing the total revenue and costs per contract of the pricing policy *Dynamic 6* over 240 months.

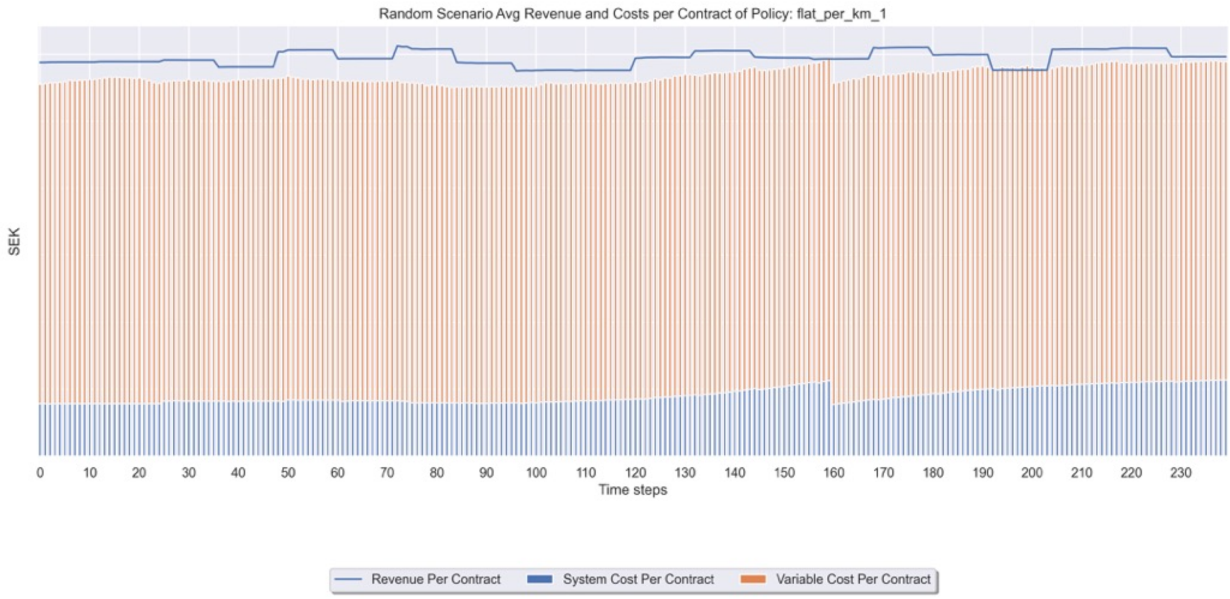

Figure 25: A random scenario showing the total revenue and costs per contract of the pricing policy *Flat Per Km 1* over 240 months.

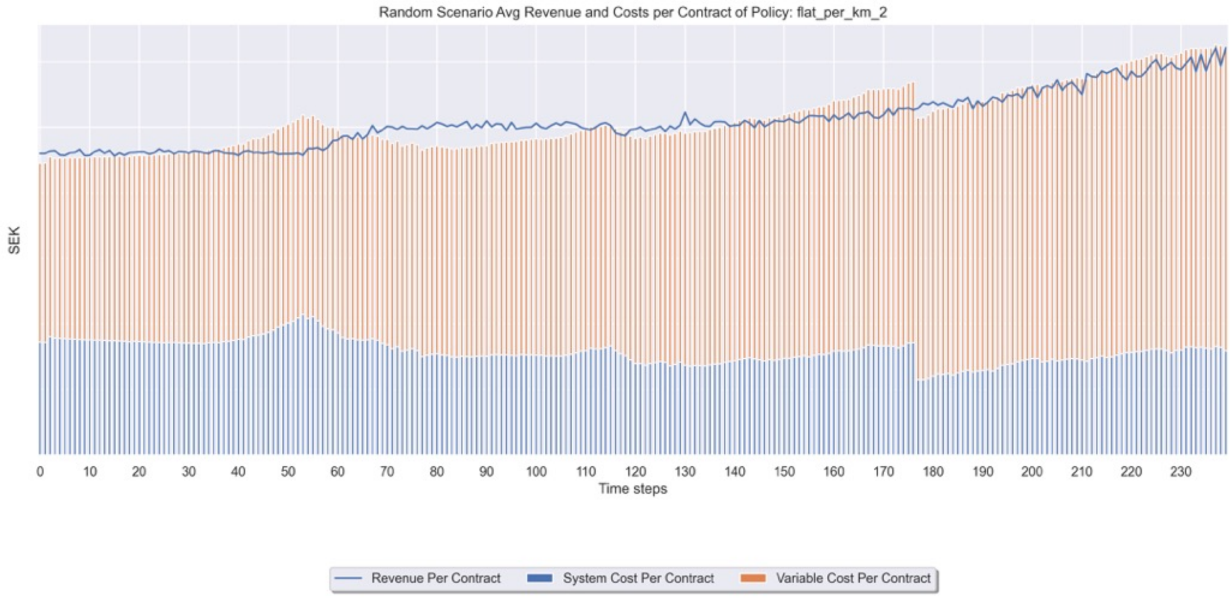

Figure 26: A random scenario showing the total revenue and costs per contract of the pricing policy *Flat Per Km 2* over 240 months.

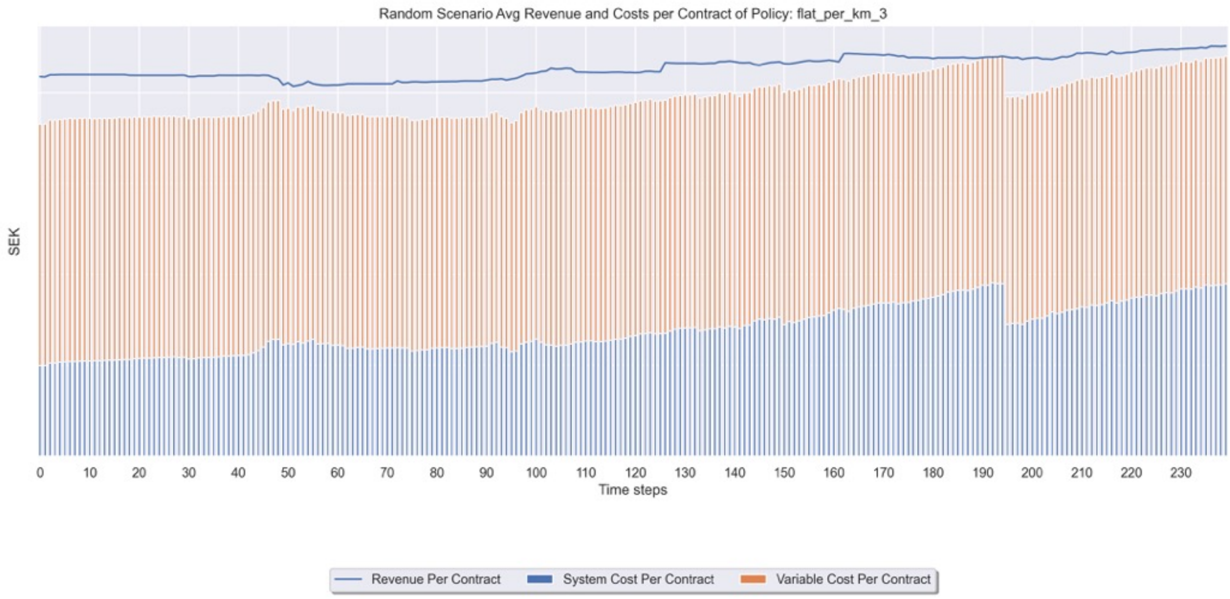

Figure 27: A random scenario showing the total revenue and costs per contract of the pricing policy *Flat Per Km 3* over 240 months.

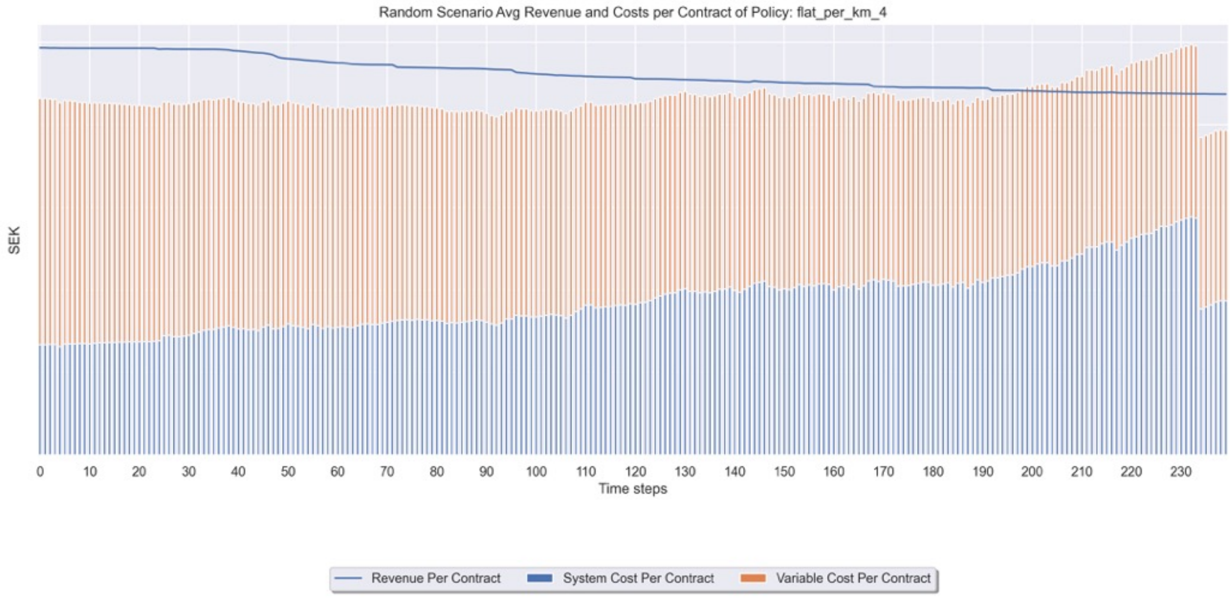

Figure 28: A random scenario showing the total revenue and costs per contract of the pricing policy *Flat Per Km 4* over 240 months.

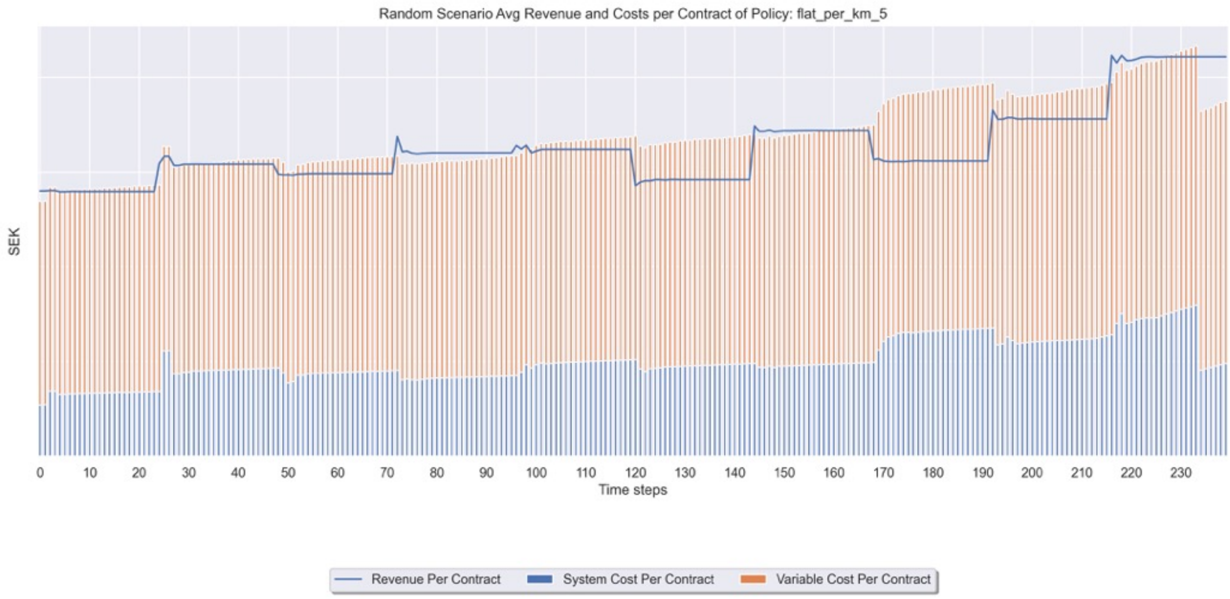

Figure 29: A random scenario showing the total revenue and costs per contract of the pricing policy *Flat Per Km 5* over 240 months.

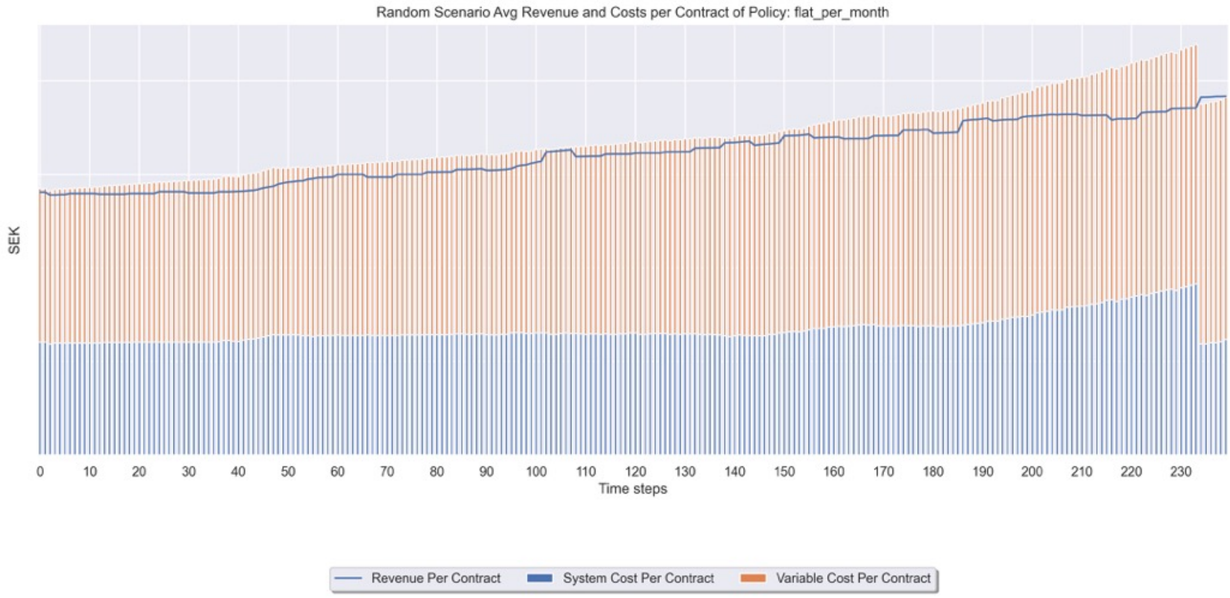

Figure 30: A random scenario showing the total revenue and costs per contract of the pricing policy *Flat Per Month* over 240 months.

E

Appendix

E.1 Outcome Distributions Per Policy

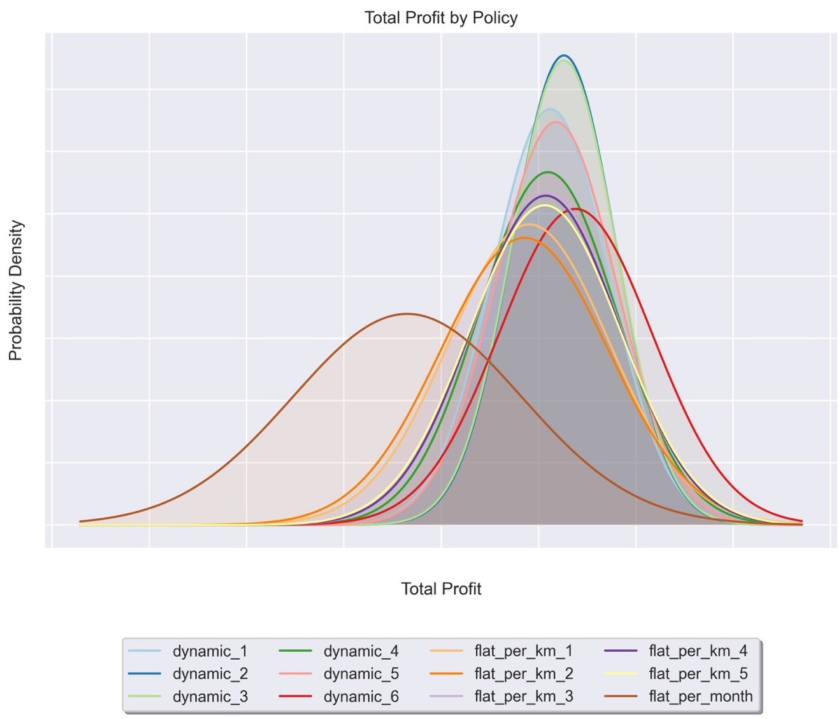

Figure 31: Normal distribution plot of the outcome Total Profit for all 12 pricing policies, using μ and σ from the outcome distribution to fit the Gaussian curve.

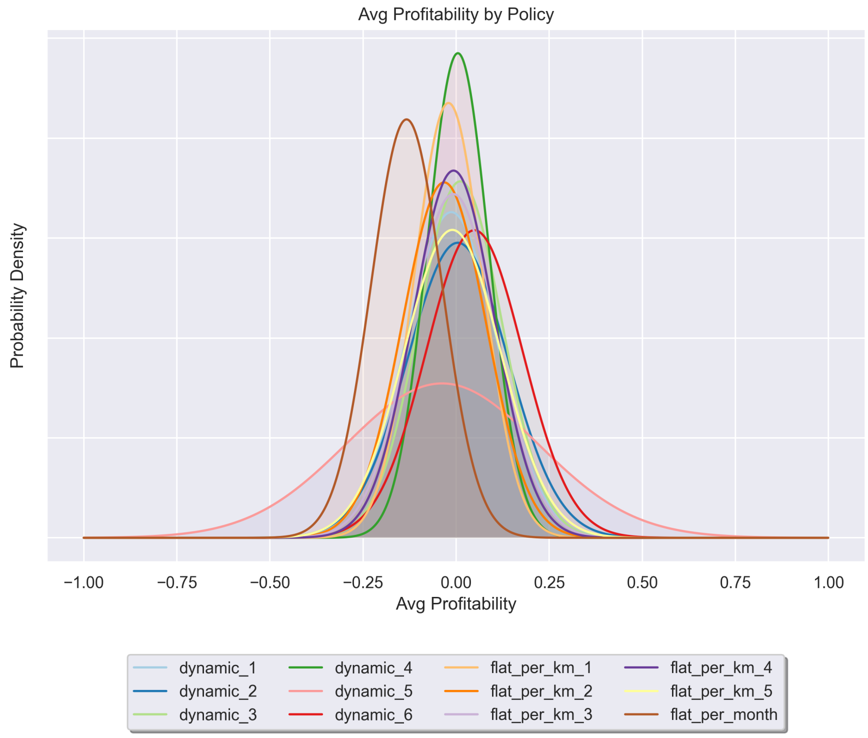

Figure 32: Normal distribution plot of the outcome Avg Profitability for all 12 pricing policies, using μ and σ from the outcome distribution to fit the Gaussian curve.

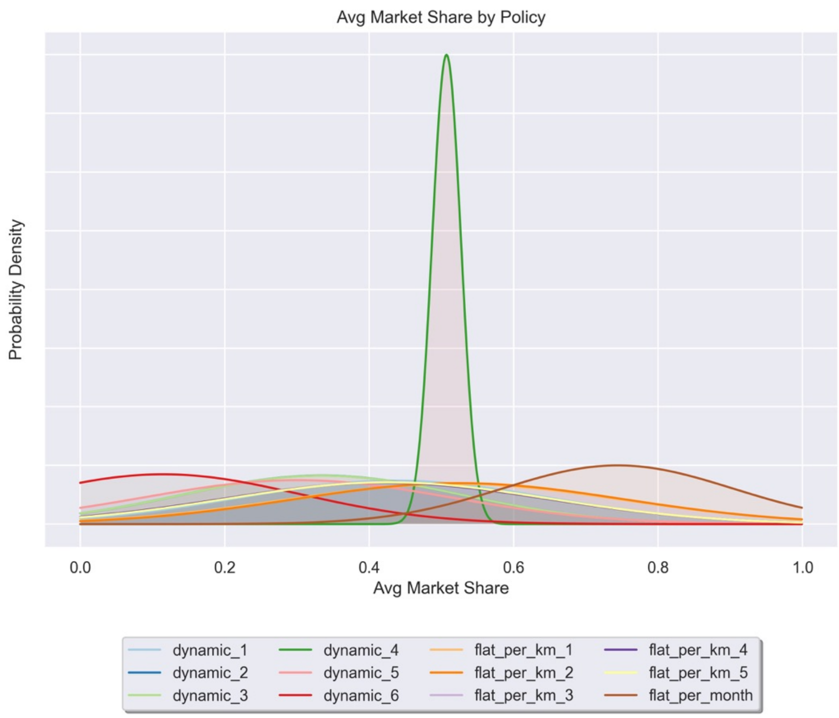

Figure 33: Normal distribution plot of the outcome Avg Market Share for all 12 pricing policies, using μ and σ from the outcome distribution to fit the Gaussian curve.

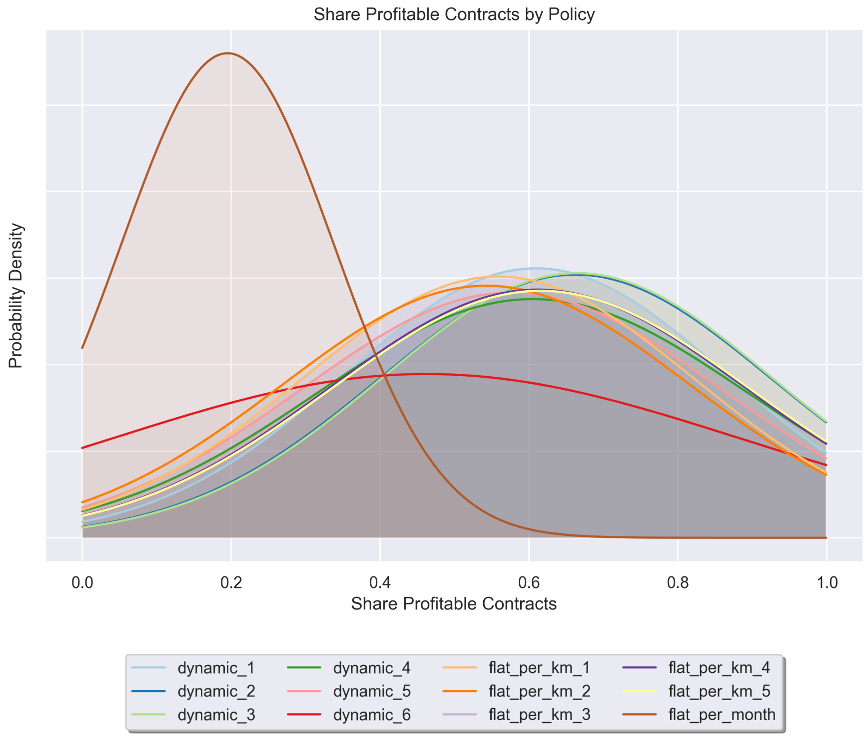

Figure 34: Normal distribution plot of the outcome Share Profitable Contracts for all 12 pricing policies, using μ and σ from the outcome distribution to fit the Gaussian curve.

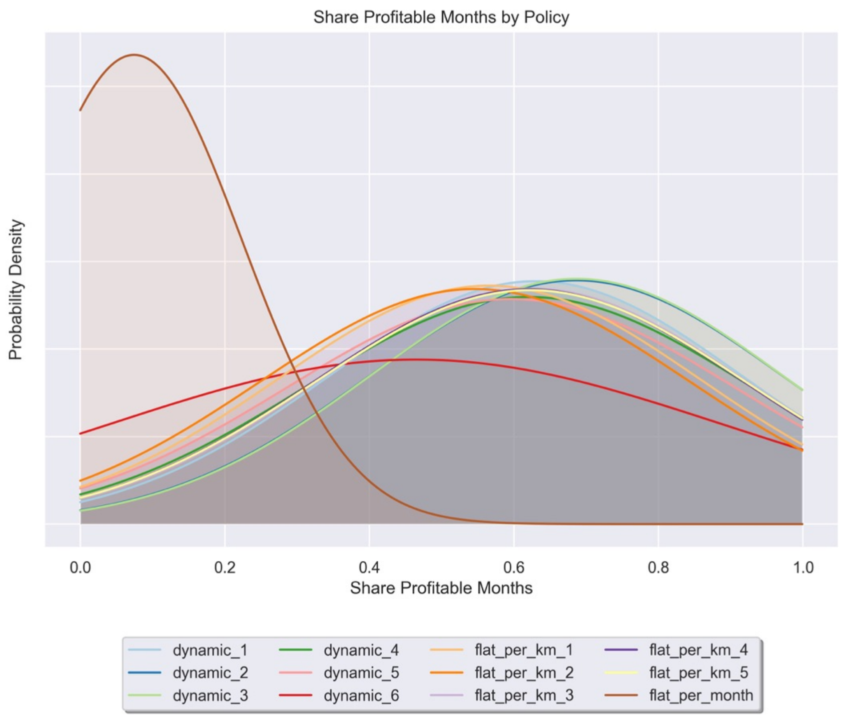

Figure 35: Normal distribution plot of the outcome Share Profitable Months for all 12 pricing policies, using μ and σ from the outcome distribution to fit the Gaussian curve.

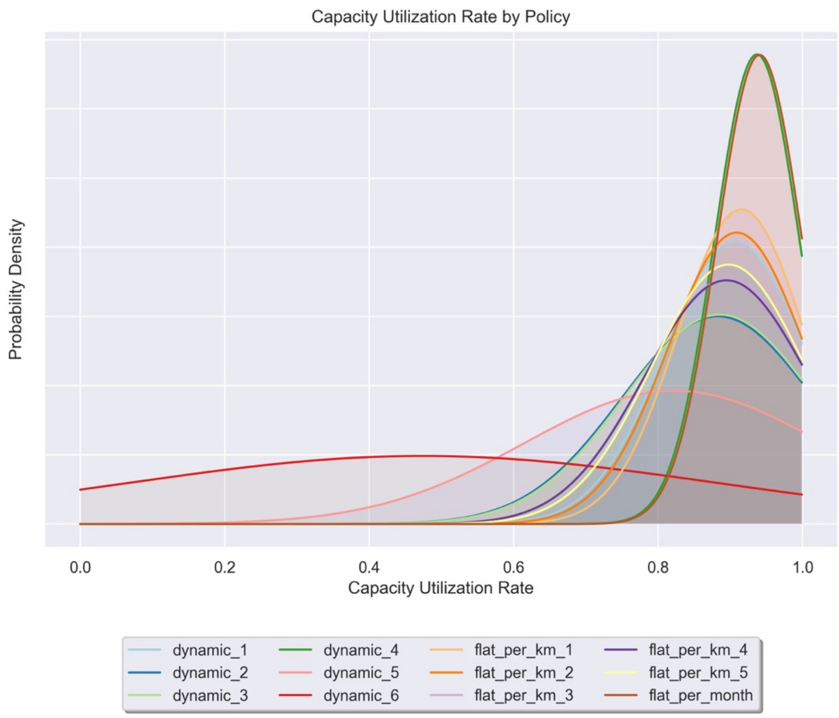

Figure 36: Normal distribution plot of the outcome Capacity Utilization Rate for all 12 pricing policies, using μ and σ from the outcome distribution to fit the Gaussian curve.

E.2 Feature Scoring: All Outcomes

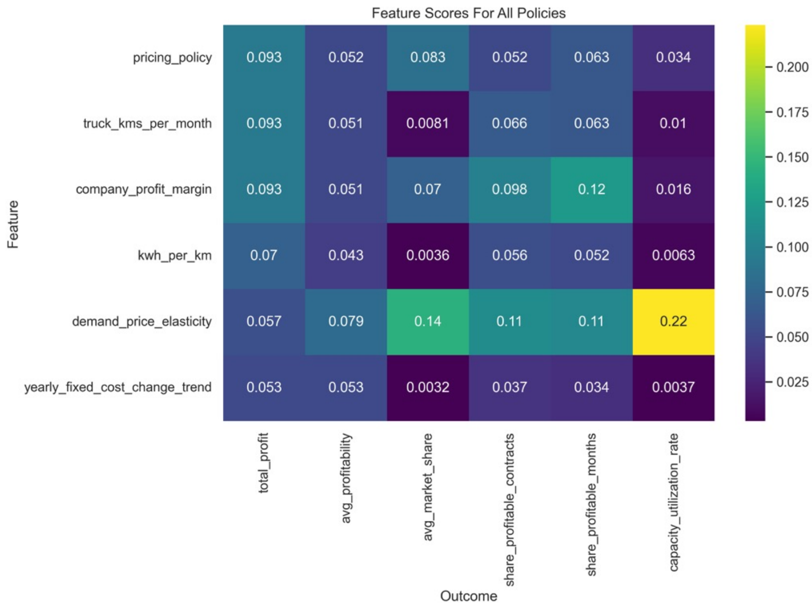

Figure 37: Most important features on outcome variance for all pricing policies.

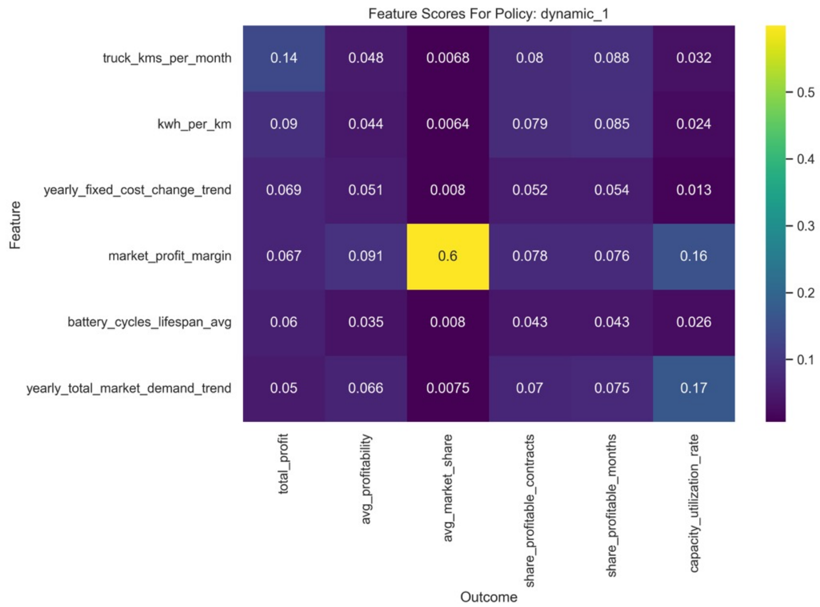

Figure 38: Most important uncertainties on outcome variance for pricing policy *Dynamic 1*.

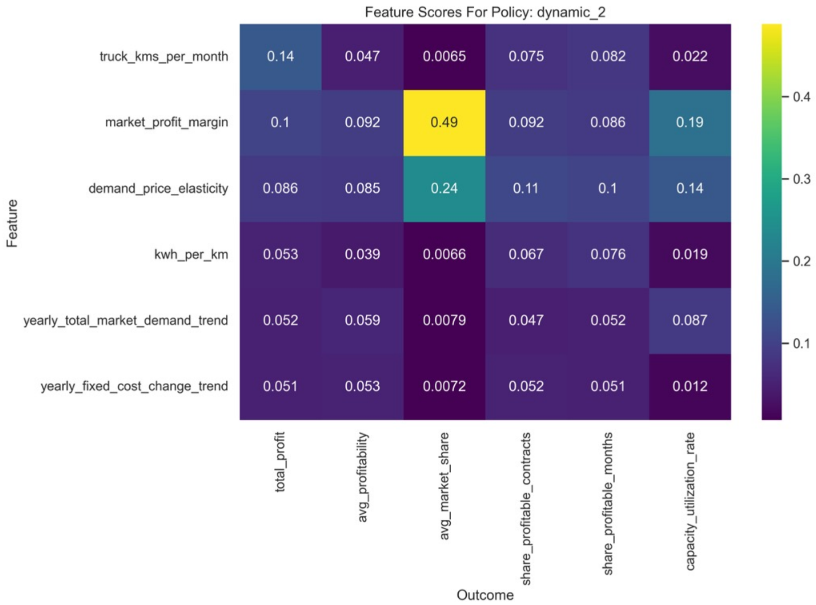

Figure 39: Most important uncertainties on outcome variance for pricing policy *Dynamic 2*.

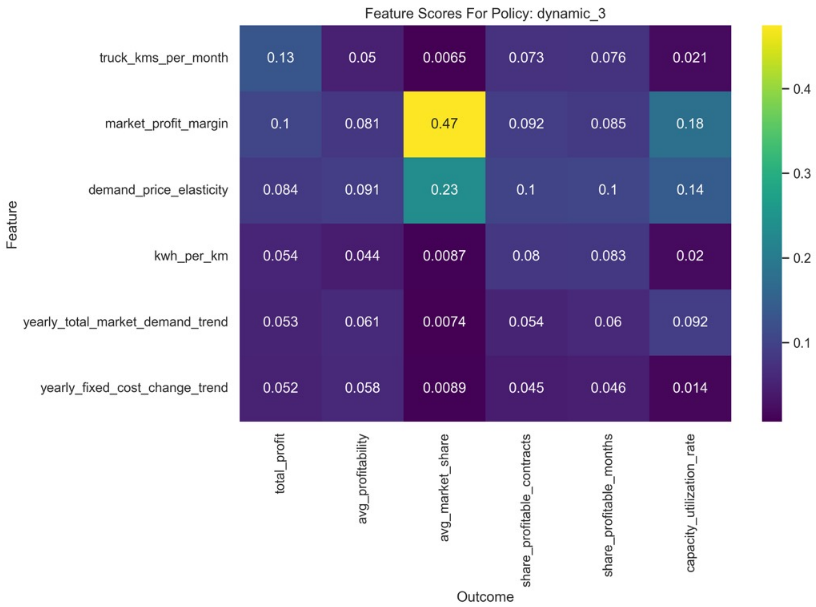

Figure 40: Most important uncertainties on outcome variance for pricing policy *Dynamic 3*.

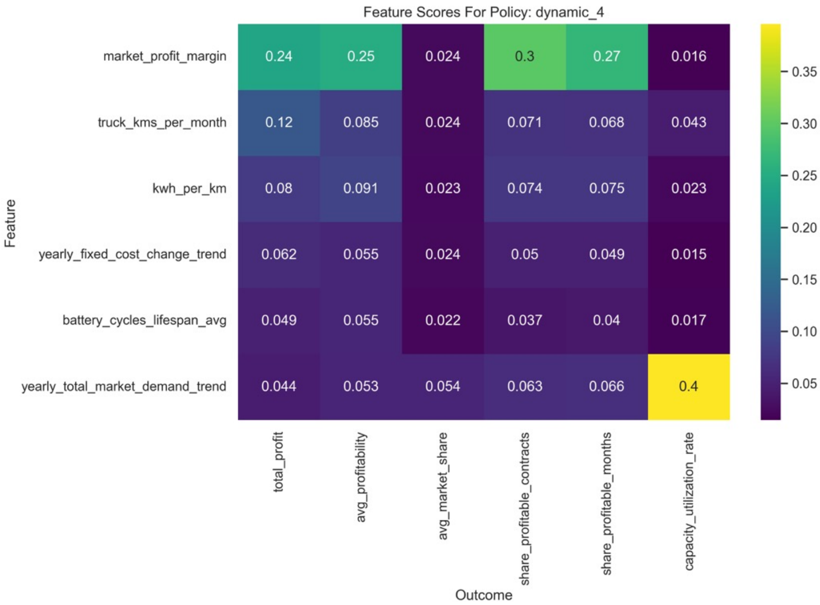

Figure 41: Most important uncertainties on outcome variance for pricing policy *Dynamic 4*.

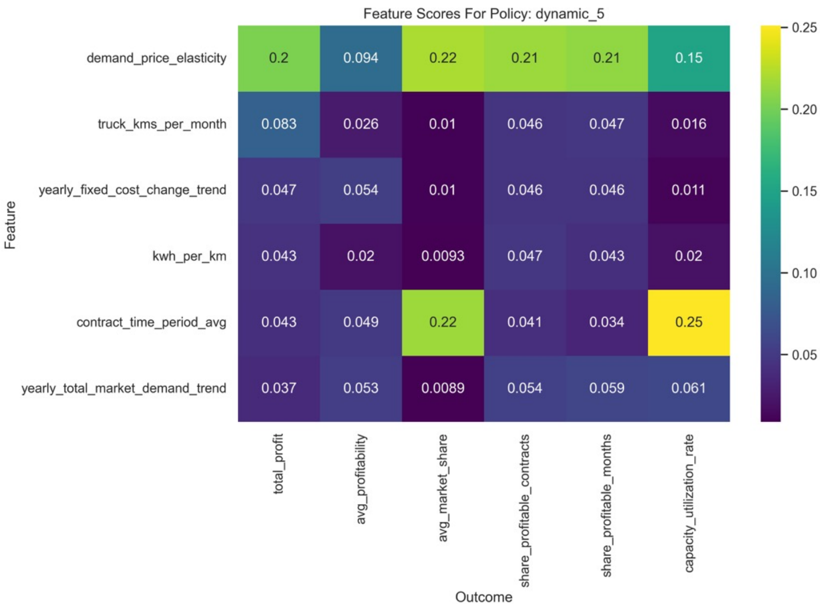

Figure 42: Most important uncertainties on outcome variance for pricing policy *Dynamic 5*.

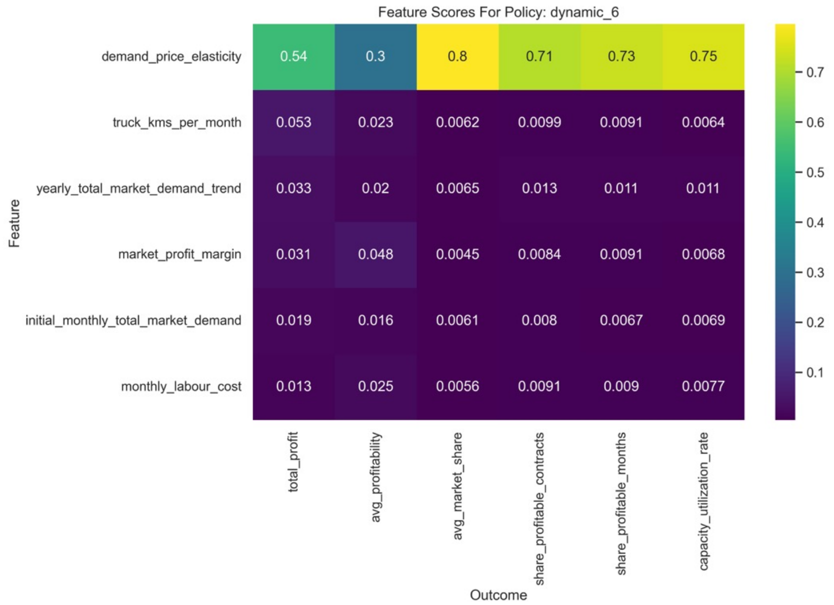

Figure 43: Most important uncertainties on outcome variance for pricing policy *Dynamic 6*.

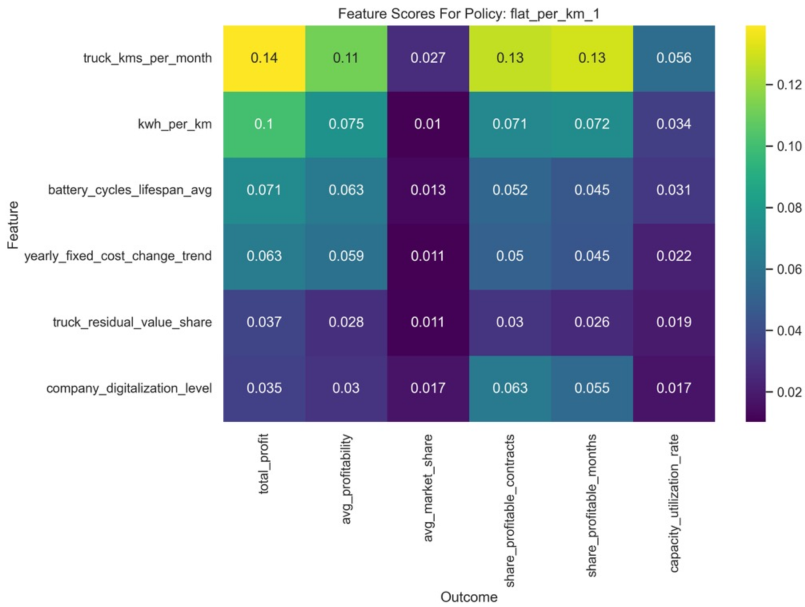

Figure 44: Most important uncertainties on outcome variance for pricing policy *Flat Per Km 1*.

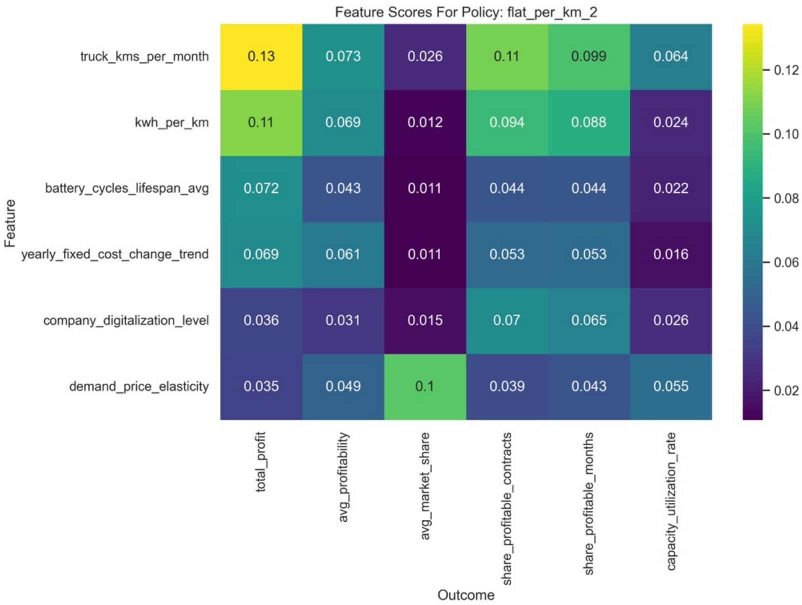

Figure 45: Most important uncertainties on outcome variance for pricing policy *Flat Per Km 2*.

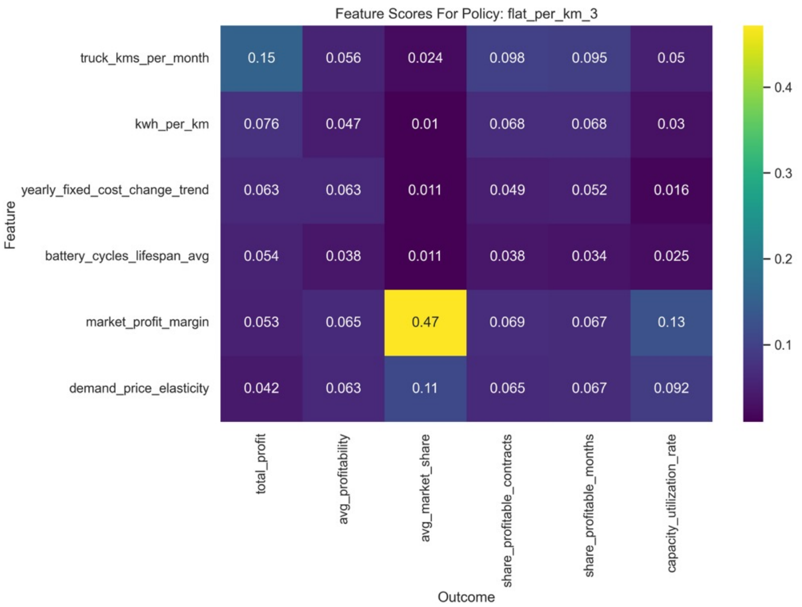

Figure 46: Most important uncertainties on outcome variance for pricing policy *Flat Per Km 3*.

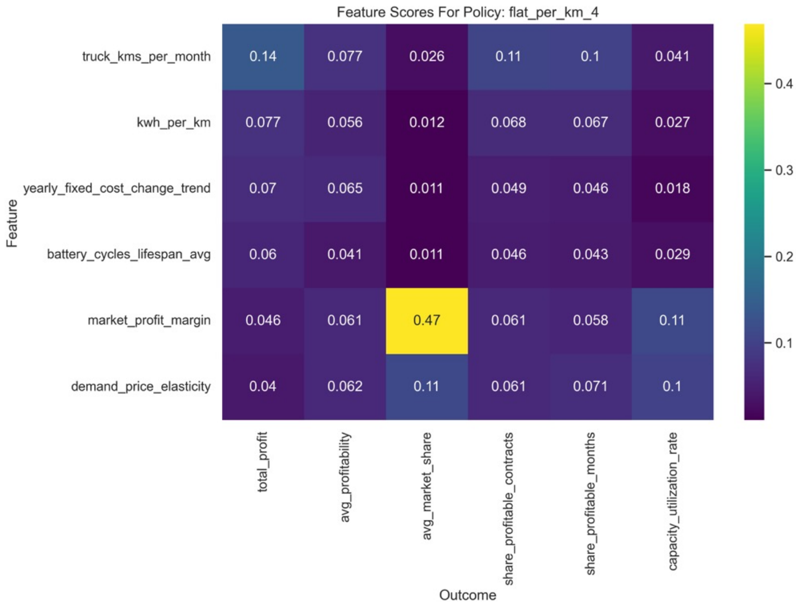

Figure 47: Most important uncertainties on outcome variance for pricing policy *Flat Per Km 4*.

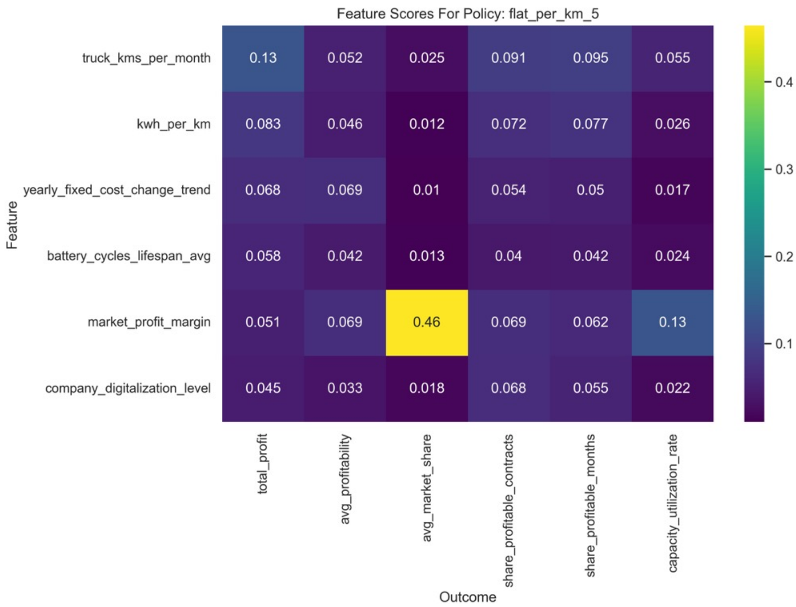

Figure 48: Most important uncertainties on outcome variance for pricing policy *Flat Per Km 5*.

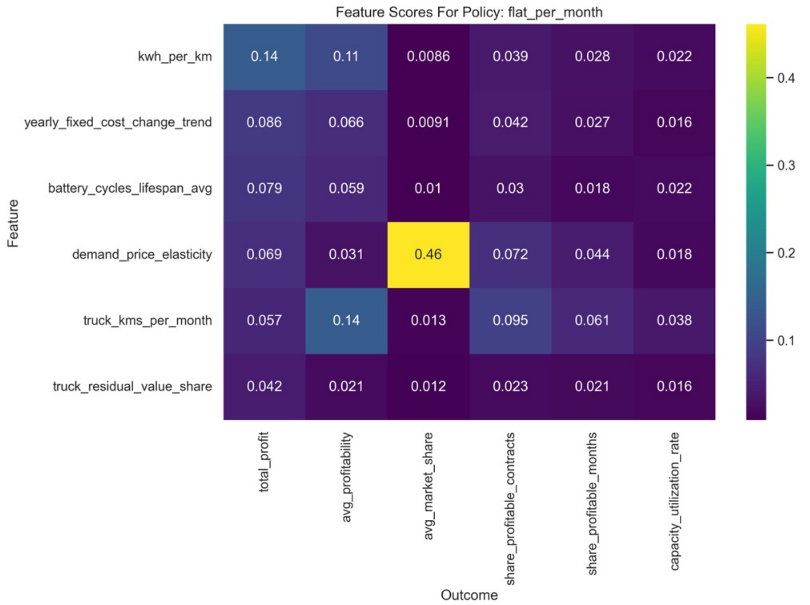

Figure 49: Most important uncertainties on outcome variance for pricing policy *Flat Per Month.*

E.3 Feature Scoring: Profitable Scenarios

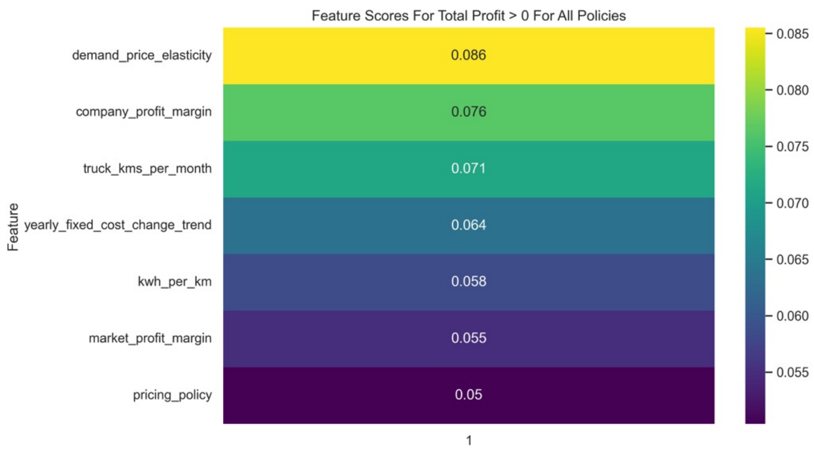

Figure 50: Main contributing features to why the total profit of an experiment turned out to be profitable or not, for all pricing policies.

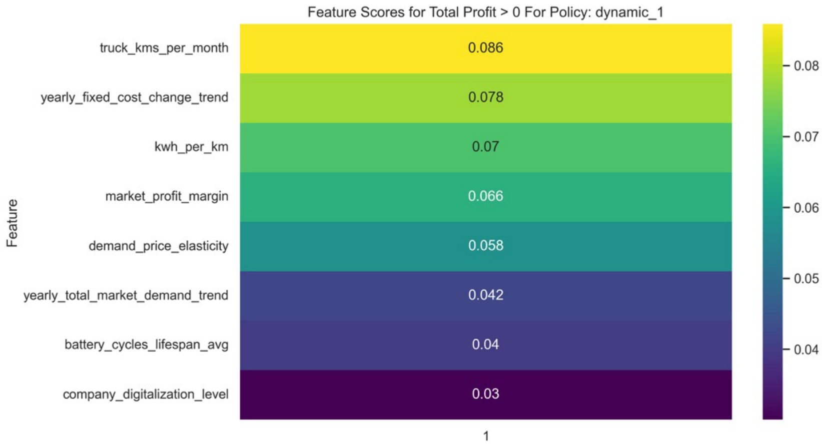

Figure 51: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Dynamic 1*.

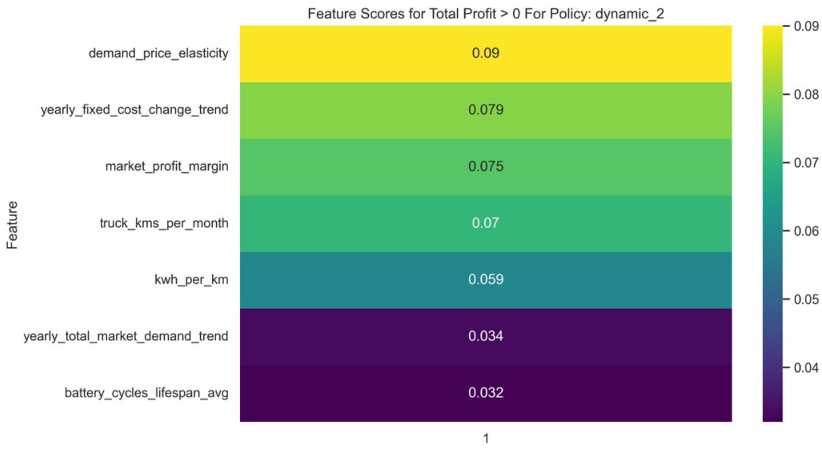

Figure 52: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Dynamic 2*.

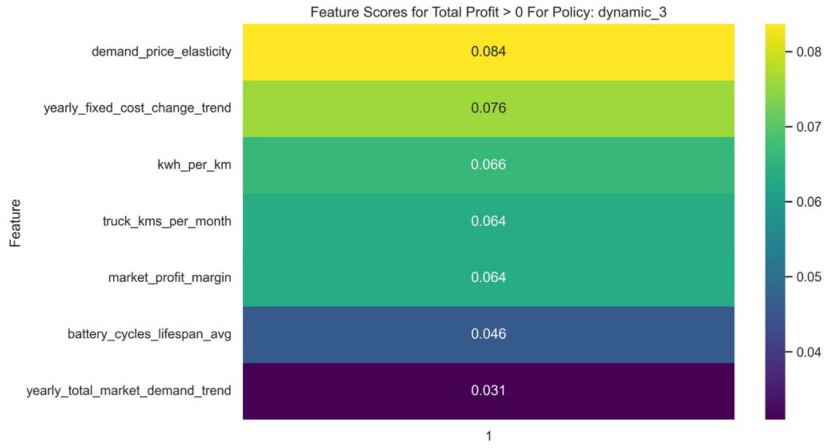

Figure 53: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Dynamic 3*.

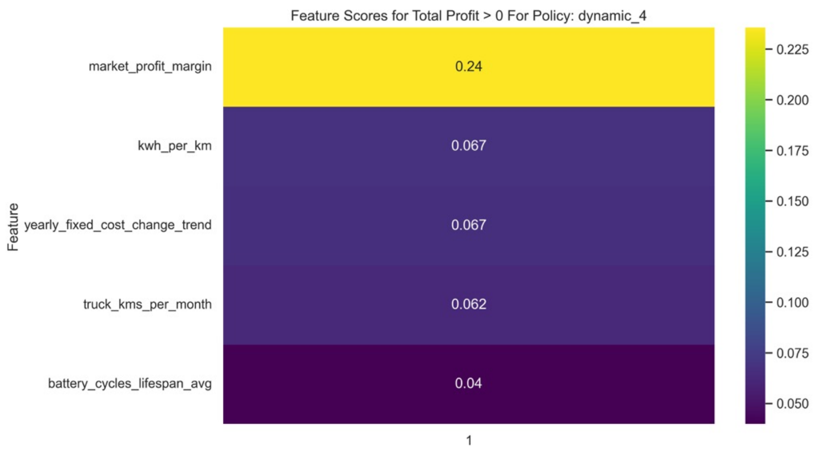

Figure 54: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Dynamic 4*.

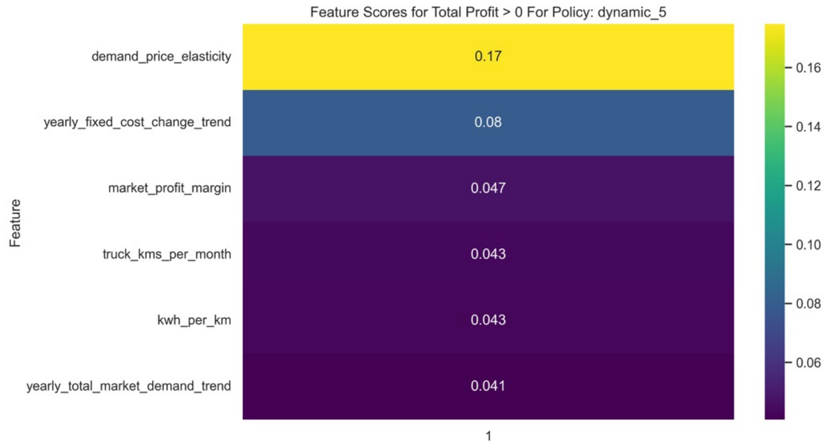

Figure 55: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Dynamic 5*.

Figure 56: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Dynamic 6*.

Figure 57: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Flat Per Km 1*.

Figure 58: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Flat Per Km 2*.

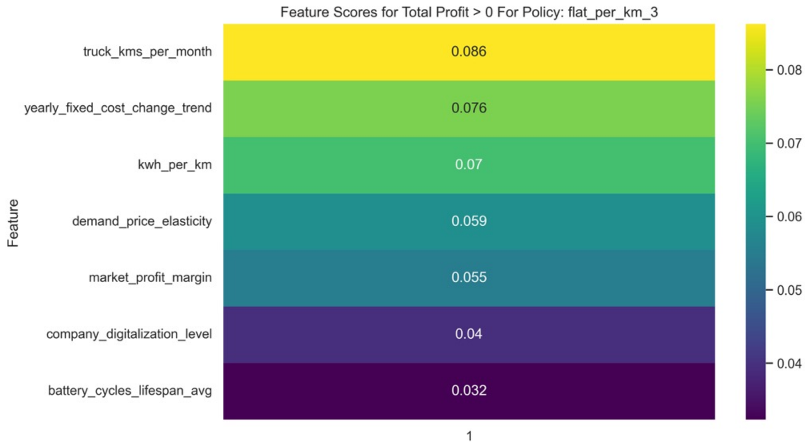

Figure 59: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Flat Per Km 3*.

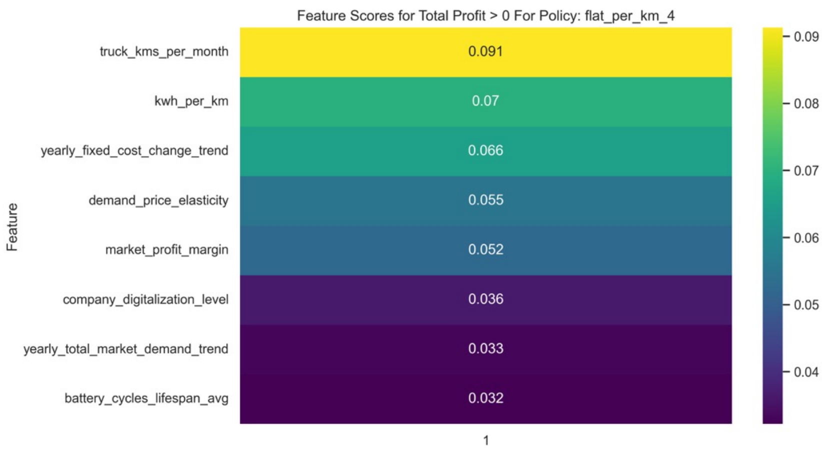

Figure 60: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Flat Per Km 4*.

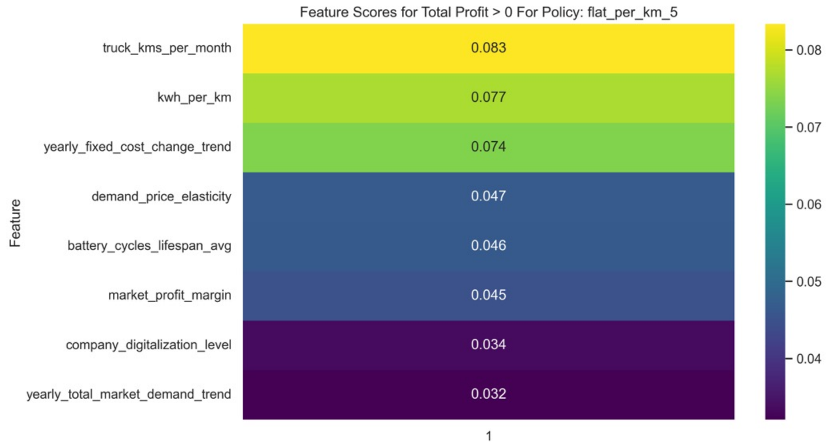

Figure 61: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Flat Per Km 5*.

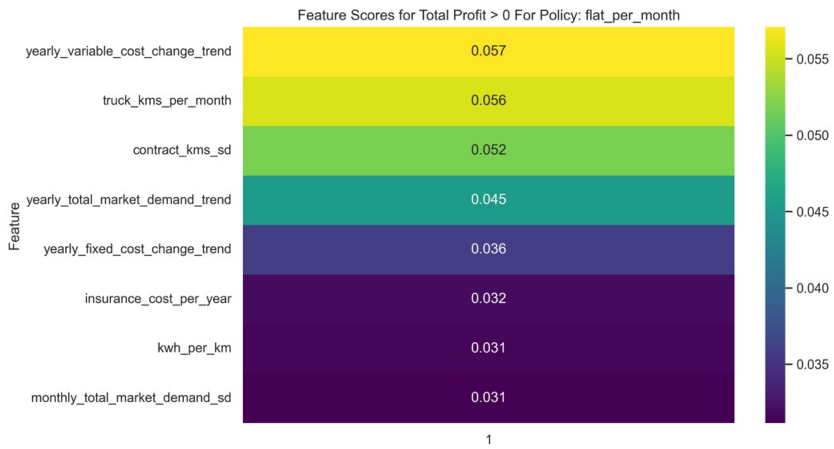

Figure 62: Main contributing uncertainties to why the total profit of an experiment turned out to be profitable or not, using the pricing policy *Flat Per Month*.

F
Appendix

F.1 Python Dependencies

Table 33: All packages and versions used for developing the Python model.

Package Name	**Version**
python	3.11
ema-workbench	2.3.0
scipy	1.10.1
numpy	1.24.2
ipyparallel	8.4.1
pandas	1.5.3
matplotlib	3.7.0
seaborn	0.12.2
pylint	2.17.1
graphviz	0.20.1
platypus-opt	1.1.0
openpyxl	3.1.2
jinja2	3.1.2

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