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Modelling and optimising the consumables supply chain of Swanage Railway

This Dissertation is submitted in part-fulfilment of the requirements for the degree of MSc. Logistics and Supply Chain Analytics

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This project is entirely the original work of student registration number 33815232. I declare that this dissertation is my own work, and that where material is obtained from published or unpublished works, this has been fully acknowledged in the references.

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ABSTRACT

This project aims to identify proactive ordering practices that can minimize costs and ensure consumables demand satisfaction, thus facilitating the Swanage Railway's daily operations. The author aimed to contribute to the implementation of a capacitated lot sizing model with two approaches including a spreadsheet for simulation-optimization of Reorder Point and a dynamic programming model developed in VBA - Excel, to account for the variability and uncertainty associated with demand and price. The first model develops a hybrid approach of simulation and optimization, to build an inventory management model based on the well-known EOQ concept. The second model analyses optimal ordering cycles considering specific conditions of maximum and minimum order quantities, limited storage capacity, and near-zero fixed ordering costs, specifically tailored for Swanage Railway. The analysis focused on examining the impact of simultaneous changes in demand season and price forecasting on the parameters that characterize inventory control activity. The model can help streamline the order process by eliminating reactive ordering and reducing the risk of out-of-stock situations. Moreover, it designed a VBA code to automatically compute the strike price value — at which the company will benefit from a fixed-price contract with a supplier. It is recommended that the Swanage Railway company pay attention to fluctuations in the coal market price and implement a more accurate forecasting model for coal prices.

Key words: Lot Sizing Model, Simulation Optimization, Dynamic Programming, Capacitated Lot Sizing Problem

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Abbreviations

Word, Phrase or Abbreviation	Definition or Expansion
CLSP	Capacitated Lot Sizing Problem
EOQ	Economic Order Quantity model
MILP	Mixed Integer Linear Programming
ROP	Reorder Point
Sim-Opt	Simulation-Optimization Model
The Company	Swanage Railway Trust, UK

Chapter 1 Introduction

This chapter discusses the project's purpose. Following the background and motivation, the aims and objectives are outlined. The research methodology is described briefly, and the dissertation structure is listed in the last section.

1.1 Background and Motivation

The relationship between inventory optimization and uncertain situations has gained considerable attention within the field of inventory management (Raj *et al.*, 2022). Inventory control is one of the most critical issues in organizational management (Vidal, 2022). According to Ziukov (2015), it is generally observed that there is no universally applicable solution due to the distinct and diverse characteristics and constraints present in each organization or firm. Historical events, including unforeseen disruptions like the recent pandemic, have underscored the pivotal role of inventory management in safeguarding businesses against volatility. These so-called "black swan" events have prompted researchers to explore robust approaches that can withstand market shocks. More specifically, the coal industry, for instance, has witnessed significant fluctuations due to factors such as escalated living costs and geopolitical tensions (Agnolucci *et al.*, 2023).

Inventory theory offers a wide range of models to assist business owners in solving inventory systems. These models are designed to address specific situations, providing managers with a variety of choices (Erkip, 2023). As the complexity of models increases to better represent real-life scenarios, the challenges associated with solving, implementing, and operating them also intensify. Certain models necessitate the utilization of high-performance computers and extensively skilled personnel with mathematical expertise. The process of choosing the most cost-effective model for solving the inventory system is a challenging task. There are several reasons why small companies often choose not to utilize inventory models to address their inventory issues. According to Wagner (1980), a significant number of the largest companies in the United States do not employ any type of operational analysis to manage their inventories. Instead, inventory policies are selected based on intuition and experience.

Swanage Railway Company are currently working on their reactive ordering process as it leads to potential disruptions and suboptimal decision-making. Additionally, the railway has experienced a substantial increase in the costs of consumables, primarily coal, oil, and diesel products, following the impact of the war. The tripled costs have put a significant financial strain on the company. Thus, conducting a thorough analysis and optimization of the supply chain, while considering the existing on-site storage constraints, becomes imperative. By employing advanced modelling techniques and optimization methods, this research aims to identify proactive ordering practices that can minimize costs and ensure consumables demand satisfaction, thus facilitating the railway's daily operations. The outcomes of this study will not only assist in streamlining the ordering processes but also contribute to the long-term sustainability and operational efficiency of the Swanage Railway.

1.2 The Company Background

The Swanage Railway Trust is a registered charity dedicated to preserving the heritage of southern England's railways, particularly those on the Isle of Purbeck in Dorset, and to re-establishing a rail link between the town of Swanage and the national rail network at Wareham. The Swanage Railway Trust focuses on advancing the development of the Swanage Railway by recruiting members and volunteers, as well as the appeals and fund-raising required to support the Trust's activities (The Charity Commission for England and Wales, 2023). The Swanage Railway is now one of the UK's largest heritage railways (Swanage Railway's Website, 2023). The Swanage Railway Company, the Trust's trading subsidiary, operates the trains and is in charge of the Railway's day-to-day operations. Even though steam haulage in southern England stopped more than 50 years ago, the Trust attempts to preserve and operate a wide range of railway equipment from that era, as well as many pieces over 100 years old.

1.3 Aim and Objectives

The **aim** of this research project revolves around optimizing the ordering processes of consumables, specifically coal ordering practices, in railway operations. The challenges arise due to limited storage space, seasonal demand variations, and the continual rise of consumables costs. The current ordering practices may not effectively address these challenges, leading to inefficiencies and increased supply chain costs. Therefore, the project seeks to develop a comprehensive optimization model that considers these constraints and aims to minimize supply chain costs while meeting the demand for consumables. The software and model proposed should be affordable and simple to implement due to the limited budget for technology development.

The **research objectives** of this project can be defined as follows:

1) To develop a mathematical optimization model: The primary objective is to develop a robust mathematical model that optimizes the ordering processes of coal and oil in the railway industry. The model should consider the constraints of limited storage space, seasonal demand variations, and predicted cost increases over a two-year time frame. The model will involve decision variables, objective functions, and constraints that enable efficient ordering decisions.

2) To incorporate the demand and price uncertainty: The research aims to incorporate the volatile nature of demand and price variables into the optimization model. By utilizing techniques such as simulation spreadsheets and dynamic programming, the model will account for the variability and uncertainty associated with demand and price. This will enable decision-makers to make informed decisions that consider multiple scenarios and their associated probabilities.

3) To validate the model and assess its effectiveness: The dissertation seeks to validate the developed optimization model using real-world data or simulations. Validation involves comparing the model's outputs with historical data, benchmark solutions, or existing practices. The effectiveness of the model will be assessed based on its ability to minimize supply chain costs while meeting the constraints of demand variability, storage limitations, and price changes.

Related **research questions** include**:**

- ❖ Can we establish how the company's current inventory control system works? Can we estimate future demand based on historical demand and ordering patterns? Can we identify key parameters (such as supply base, unit costs, and capacity constraints) and their values over time?

- ❖ How can the inventory control system of the company be improved? Can we utilise standard inventory models from the literature? How would these models need to be tailored to the specific characteristics of the company?

- ❖ In what other ways could the company reduce the cost associated with consumables? For example: what would be the value of a long-term fixed-price contract?

By addressing these research objectives and research questions, this study aims to provide valuable insights and recommendations to the Swanage Railway company, enabling them to optimize their ordering processes, minimize costs, and enhance operational efficiency.

1.4 Methodology

The models will be developed based on real-world data and industry knowledge. To assure the models' accuracy and reliability, historical demand data, pricing information, storage capabilities, and other relevant data sources will be used. The models' outputs will be validated by comparing them to previous findings, scenarios testing, and comments from industry supervisors. This rigorous validation approach will ensure that the models generate credible and actionable ordering recommendations.

The research employs both qualitative and quantitative methodologies. A detailed literature review and a brief review of the company's inventory management can explain the aspects that influence inventory ordering practices. The overall goal of this research study is to compare two different methods for reducing supply chain costs. These models aim at optimizing inventory and order placement decisions for highly volatile consumable products with limited storage space, such as coal, under probabilistic demand and price fluctuation. The first model develops a hybrid approach of simulation and optimization, with a view to building a inventory management model based on the well-known EOQ concept and (s, S) reorder point model. The second model based on Wagner-Whittin Dynamic Programming. The two models are investigated while incorporating the capacity constraints and ensuring that there is no stock-out during the planning horizon.

1.5 Dissertation Structure

The dissertation is structured as follows.

In Chapter 2, the focus is on the extensive literature review, delving into the historical aspects of inventory management, the evolution of inventory models, and the techniques adopted to solve these problems.

Chapter 3 encompasses the research methodology, elucidating the thorough analysis of the Swanage Railway Company's inventory operations, the process of data collection and preprocessing, as well as the methodologies employed for demand forecasting and solving Swanage Railway's ordering problems. This chapter further describes the algorithms behind the two models: The Simulation-Optimization model and the Dynamic Programming Model and how they are developed to fine-tune with the Company's characteristics.

Chapter 4 presents the results derived from the developed models under various numerical experiments found on the given framework methodology in the previous chapter, as well as highlights the significant findings associated with helping the manager in coping with price and demand uncertainty.

In Chapter 5, the discussion highlights the strengths and limitations of each model. Additionally, suggestions are made for the applicability of the two models as well as their ability to be replicated in the future.

Chapter 6 concludes the dissertation with a well-rounded summary of the findings, engaging in a thoughtful discussion surrounding the limitations encountered during the research process. This chapter also acts as an opportunity to suggest intriguing directions for future research.

Chapter 2 Literature Review

In this chapter, core concepts and techniques around inventories and inventory management will be discussed, with a view to identifying which approaches could be most valuable to meet the aim and objectives of this study.

2.1 Role of Inventory

Inventory can be described as a “physical stock of goods kept in store to meet the anticipated demand” (Vrat, 2014, p. 21) and it plays a crucial role in the supply chain. Moreover, holding inventory is crucial for maintaining efficient operations in manufacturing organizations. Inventory consists of raw materials, goods in process, and finished goods (Atnafu *et al.,* 2018). Gurtu (2021) stated that inventory items vary across organizations based on factors such as the nature of their business operations (e.g., manufacturing, trading, retail) and the specific industry they operate (e.g., automotive, healthcare, construction).

While the benefits of holding inventory have been widely acknowledged, recent literature has drawn attention to its drawbacks, particularly with regard to the adverse impact that this may have on supply chain responsiveness (Chopra & Meindl, 2012). The accumulation of high inventory levels can impose adverse effects on both cash flow and warehousing capacity. In opposition to this approach, proponents of lean inventory management advocate for reduced inventory levels and the adoption of just-in-time principles. This approach emphasizes several advantages such as improving cost-effectiveness (Arif-Uz-Zaman & Nazmul Ahsan, 2014), reducing waste (Shah & Ward, 2003) and facilitating the responsiveness of the company to changing market demands and decreasing surplus inventory during low demand (Balkhi *et al.*, 2022).

Nevertheless, the perspective that views inventory as an "idle resource" suggests that holding inventory merely immobilizes the company’s capital (Vrat, 2014). Furthermore, Sople (2010) also indicated that too much capital is held up on stocked items. Similarly, Jacobs and Chase (2014) elucidate that the presence of inventory incurs several costs.

These include Setup costs, Ordering costs and Holding costs. A more detailed discussion of these costs is provided in section 2.2.2.

The holding costs of inventories in a supply chain are estimated to range from 20% to 60% (Baker, 2007) and from 25% to 55% of the total value of company assets (Zahran *et al.*, 2017). Therefore, effectively managing inventory is advantageous for a company's financial performance (Atnafu *et al.*, 2018).

2.2 Inventory Management and Inventory Control

Inventory modelling has received considerable research attention in the field of operations management and operations research (Rumyantsev & Netessine, 2007). Inventory management and inventory control have different scopes and objectives.

2.2.1 Inventory Control

Inventory control is a cost-effective approach that involves the acquisition and storage of materials in a manner that minimizes disruptions to production and distribution schedules. Similarly, Schönsleben (2000) defined Inventory control as a systematic method used to determine the optimal quantity, timing, and selection of items to be procured and maintained in stock for a specified period. According to Lee and Billington (1993), inventory control plays a vital role in ensuring the stability and resilience of the supply chain. Inventory control aims to optimize inventory usage by reducing costs through strategies such as minimizing purchases of slow-moving products and monitoring demand fluctuations to prevent stock-outs or overstocking (Goltsos *et al.*, 2022).

Inventory control revolves around three fundamental questions (Silver, 1981):

1) What is the recommended frequency for inventory status checks?

2) When is the appropriate time to make a purchase?

3) What is the recommended number of orders to be placed?

Harris (1913) conducted the pioneering academic study on inventory control, specifically focusing on the concept of "lot sizing". The study was motivated by the author's professional background in optimizing replenishment order quantities (Ma *et al.*, 2019). Harris (1913) relies on several assumptions about demand and production capacity in order to formulate the total cost equation for the commodities being produced. The assumption is that demand is independent, continuous, and constant. The researcher examined the relationship between total cost and order size and developed the square-root formula for determining the optimal quantity to reorder (Chua & Heyward, 2017). This formula, known as Economic Order Quantity (EOQ), is used to solve the deterministic lot sizing problem.

Extensive research has been conducted on lot-sizing models, which have evolved over time to incorporate more realistic assumptions (Ma *et al.*, 2019). Several versions were created as a result of varying demand characteristics and parameter choices. Section 2.3 provides a comprehensive examination of frequently employed inventory models.

2.2.2 Inventory Management

Inventory management is a critical aspect of supply chain operations and has a profound impact on a business's efficiency, profitability, and customer satisfaction (Singh & Verma, 2018). A well-executed inventory management strategy helps strike a balance between having sufficient stock to meet customer demand and minimizing holding costs (Mitrović *et al.*, 2021). This literature review explores various factors that influence inventory management practices, including financial considerations, supplier relationships, lead times, and external factors.

Financial Factors

The cost of inventory is a significant financial consideration for businesses. Chan *et al.* (2017) outlines several common inventory management strategies, all of which depend on factors like the quantity to be procured, the stock level at which orders are placed, the time between procurements, and the maximum allowed quantity of stock. Three main types of financial parameters which are commonly incorporated into these strategies are described below. Monitoring these financial factors helps businesses plan their spending and adapt their inventory management strategies accordingly.

- ❖ **Setup costs** involve the expenses required for launching production, that include administrative tasks, procurement of materials, and equipment preparation.
- ❖ **Ordering costs** refer to the fixed costs associated with placing an order for an item. The costs are not dependent on the quantity ordered, but rather on the activities involved in processing the order (Leandro *et al.*, 2021).
- ❖ **Holding costs** consist of not only storage costs but also financial costs associated with the capital tied up in inventory. This can include handling fees, insurance, and costs related to storage facilities (Chopra & Meindl, 2012). Fluctuations in the cost of interest rates, and tax expenses can significantly influence inventory management (Vries, 2013). For example, higher interest rates can increase borrowing costs and, in turn, holding costs.

Supplier Relationships

Supplier relationships play a pivotal role in inventory control. It is important to consider supplier delays as they can have a significant impact on procurement objectives, particularly in terms of on-time delivery. When these delays are not accurately estimated, it can result in a shortage of inventory and ultimately disrupt the manufacturing process (Hong *et al.*, 2018). According to Barros *et al.* (2021), businesses are encouraged to establish backup sources to mitigate the impact of supplier-related uncertainties. Evaluating supplier performance, delivery times, and consistency is essential for effective inventory management. Furthermore, understanding supplier dynamics, such as lead times, order processing times, and minimum order quantities, is crucial for maintaining optimal inventory levels (Chang & Lin, 2019).

Lead Time

Lead time, the duration between placing an order and receiving it, has a direct impact on inventory management (Cachon & Terwiesch, 2013). Longer lead times necessitate higher inventory levels to meet customer demand while awaiting replenishments. Stochastic lead times, where delivery times vary, add an extra layer of complexity. As Zipkin (1989) suggests, both the mean and variance of lead times influence the amount of inventory a company must hold. Understanding the relationship between lead times and inventory levels is vital for efficient inventory management.

External Factors

External forces that are beyond a business's control emphasize the importance of ongoing monitoring and adaptation in inventory management practices (Chan *et al.*, 2017). For instance, economic downturns can cause unpredictable changes in demand (Chopra & Meindl, 2012). Staying informed about economic conditions is essential to prevent stock shortages or excessive inventory accumulation.

2.3 Inventory Models

2.3.1 Classification of Inventory Models

According to Brunaud *et al.* (2019), the determination of an optimal ordering plan for a specific time period involves simultaneously determining the inventory levels at storage facilities. This is because the multi-period planning models incorporate inventory balance constraints, as discussed by Bradley and Arntzen (1999). These statement leads to an assumption that with a demand forecast, it is feasible to determine the precise timing and quantity of inventory replenishments. In practice, warehouses are managed based on policies which specify when and how much inventory should be replenished. A holistic view of some of the attributes in distinguishing between various inventory policies is given in Figure 1.

Two replenishment policies commonly used in practice are continuous review and periodic review (Setyaningsih & Basri, 2013). Under the Periodic review policy, stocks are replenished on specific days of the week and the inventory is reviewed at specific intervals. The decision regarding whether to place a replenishment order and the quantity of the order are contingent upon the current inventory level at the time of review.

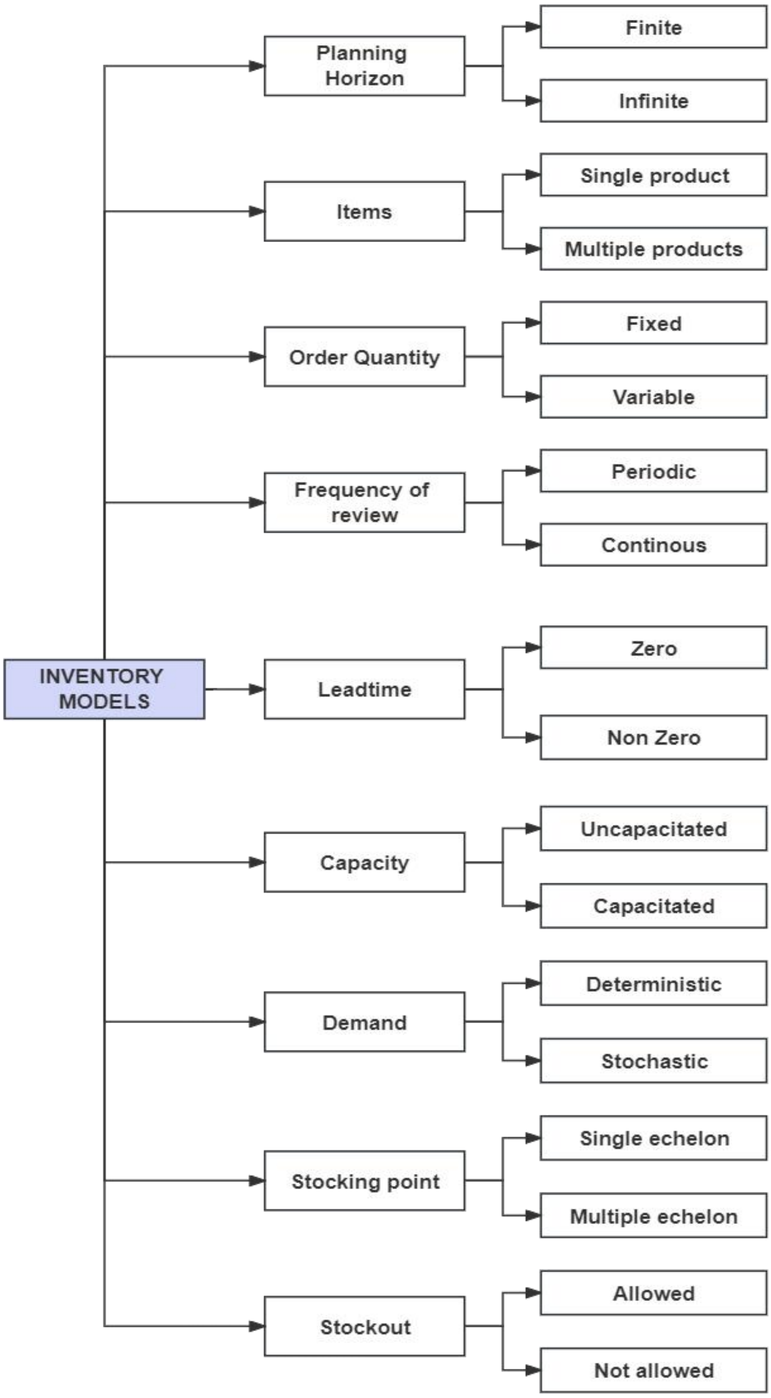


Figure 1 Classification of inventory model

(Source: Ullah & Parveen, 2010)

Continuous review involves the ongoing monitoring of inventory status, with orders being placed based on lot size (Q) when the inventory level reaches the predetermined reorder point (ROP). However, Brunaud *et al.* (2018) questioned the approach of continuous monitoring of inventory levels as the authors stated that it may not be feasible or viable in numerous applications. Similarly, Yousef (2014) states that the Continuous review policy is primarily employed for high-value products due to the significant cost associated with keeping them in stock. This policy can also be applied in situations where suppliers demonstrate high flexibility in terms of timing and order quantity. Therefore, the researchers suggested a method of checking when the inventory falls below a certain threshold, an order is placed to restore the inventory to a specified base stock level. This model is also known as the Reorder Point policy.

Generally, inventory models can be divided into two categories: deterministic models and stochastic models based on the nature of demand (Glock *et al.*, 2014). Types of demand could be classified as it is shown in Figure 2.

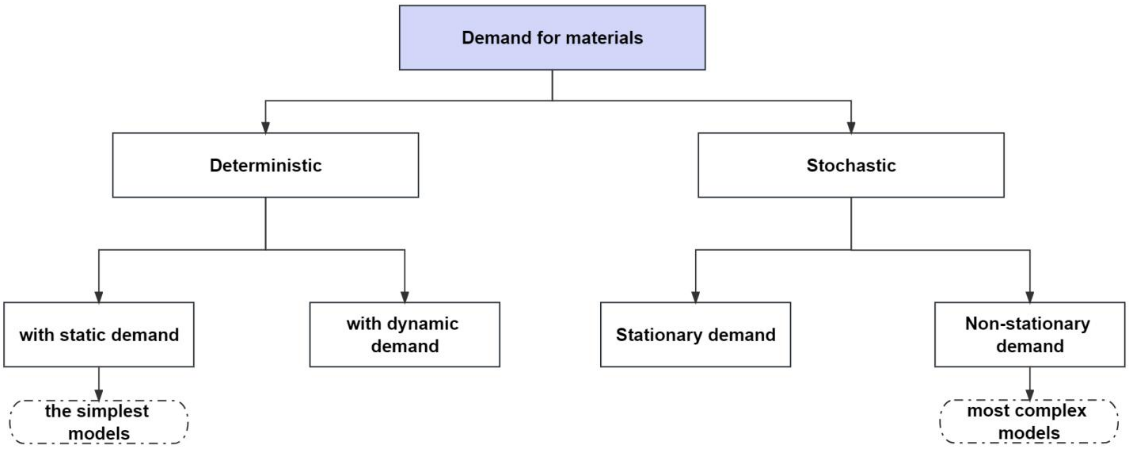


Figure 2 Classification of demand input for inventory models

(Source: Kazaryan & Andreeva, 2020).

According to Ziukov (2015), deterministic demand is characterized by precise and known values, in contrast to probabilistic demand. There are two types of deterministic demand models. One category is characterized by being static, meaning that this type of demand is either already known or can be accurately calculated. The second type is characterized by its dynamic nature, meaning that it has the potential to change or vary. The demand for this type of product fluctuates over time, but the specific patterns of how the demand changes are well-established and predictable.

2.3.2 Lot Sizing Problem

Lot sizing is one of the most crucial and challenging topic in production planning (Karimi *et al.*, 2003). Lot sizing specifies the quantity of time and product to be produced in order to reduce total costs. Discrete lot sizing is a technique that allows lot sizes to vary over time, depending on the demand and cost factors (Gutiérrez *et al.*, 2008). Table 1 summarizes the previously briefly stated information about lot-sizing procedures for greater clarity.

Table 1 Summary of lot-sizing methods

(Source: Florim et al., 2019)

Method acronym	Method name	Formula(s)	Comments	Reference
LFL	Lot-for-lot	-	Perhaps the easiest approach to lot sizing	Silver et al., 1998
EOQ	Economic Order Quantity	$EOQ = \frac{\sqrt{2AD}}{H}$	D – Demand rate of the item A – Ordering cost H – Carrying cost	Harris, 1913; Silver et al., 1998
POQ	Periodic Order Quantity	$POQ = \frac{EOQ}{\overline{D}}$	EOQ – Economic Order Quantity $\overline{D}$ – Demand rate of the item (average)	Silver et al., 1998
S-M or LPC	Silver-Meal or Least Period Cost	$TC\ (T) = \frac{(\text{Ordering Cost}) + (\text{Total carrying costs to end of period } T)}{T}$	T – Number of periods of the replenishment TC – Total Cost (for T periods)	Silver et al., 1998
LUC	Least Unit Cost	-	Heuristic very similar to the Silver-Meal heuristic	Silver et al., 1998
W-W	Wagner-Whitin	$C_{t,N+1} = \min\{E_{t,k} + C_{k,N+1}\}$ $t = N,\ldots,2,1$ $t < k \leq N+1$	A dynamic programming model with O(n2), which aims at obtaining the optimal order quantities, i.e. the lot size that minimizes the total costs	Wagner and Whitin, 1958

One of the most widely used algorithms for discrete lot sizing is the Wagner-Whitin (1958) algorithm. This algorithm is a dynamic programming approach that finds the optimal lot sizes for a given planning horizon, assuming that the demand, set-up cost, and holding cost are known and constant for each period. The algorithm iterates from the final period and continues this process until reaching the first period. The value of order quantity is chosen for each period based on the lowest total cost, as described by Wagner & Whitin (1958).

Although the algorithm guarantees finding the optimal solution, one of the main disadvantages of using the Wagner-Whitin algorithm for discrete lot sizing is that the algorithm requires a lot of data input and processing, and may not be suitable for dynamic or uncertain environments, where the demand, cost, or other parameters may change frequently or unpredictably. Considering the limitations of the Wagner-Whitin algorithm for discrete lot sizing, many other methods and models have been developed and proposed.

Heuristic methods, such as the Silver-Meal heuristic (1973), or the Least Unit Cost heuristic, are simple rules or formulas used to determine lot sizes without searching for an optimal solution (Florim *et al.*, 2019). Though they are typically faster and easier to implement, they may not be very accurate or efficient.

Numerous studies have been conducted over several decades to explore lot-sizing models and incorporate further realistic assumptions (Ma *et al.*, 2019). This resulted in multiple variations based on demand characteristics and parameter settings. The assumption of deterministic demand is generally considered reasonable. In Axsäter's (2015) study, three reasons are discussed as to why companies may encounter situations where they face predictable demand, such as fulfilling long-term contracts. In these cases, it is often possible to use deterministic lot sizing.

However, even when dealing with uncertain demand, determining the appropriate lot size should involve finding a balance between the costs associated with ordering and holding inventory. In practical applications, it is common to begin by substituting the uncertain or random demand with its average value. This allows for the use of a deterministic model to calculate the appropriate lot size. The next step involves utilizing a stochastic model to calculate the reorder point (ROP) based on the given lot size (Axsäter, 2015).

The Reorder Point (ROP) refers to the specific moment or inventory level at which it becomes necessary to place an order for goods in order to ensure timely restocking and distribution (Efrilianda *et al.*, 2018). According to Jacobs and Chase (2014), the inventory level is continuously monitored and a replenishment order for a fixed quantity, Q, is placed when it reaches the ROP. Moreover, they stated that the most commonly used approach for determining the timing and quantity of orders is a ROP system combined with Economic Order Quantity (EOQ). The order-up-to model is a strategic inventory management approach specifically designed for products with frequent replenishments and a long-term outlook (Cachon & Terwiesch, 2013)

2.3.3 Capacitated Lot Sizing Problem

The Capacitated Lot Sizing Problem (CLSP) is developed based on the Wagner-Whitin problem, extending the basic lot sizing problem to account for capacity constraints. The Wagner-Whitin model can be seen as a simplified version of the CLSP where capacity constraints are not explicitly considered. In other words, the Wagner-Whitin model assumes that you can produce as much as needed in each period without any capacity limitations. This makes the CLSP a more realistic representation of manufacturing situations where there are finite resources or capacity limits, such as machine time, labour, or warehouse space (Gicquel *et al.*, 2008). In summary, CLSP models seek to identify a production schedule that balances set-up and inventory holding costs, while also considering capacity constraints and ensuring that all product demand is met without backlog.

2.3.4 Optimization Methods

The CLSP belongs to the class of NP-hard combinatorial optimization problems (Glock *et al.*, 2014). Over the years, researchers and practitioners have explored various optimization approaches to tackle the CLSP, with a focus on achieving both accuracy and computational efficiency (Ramaekers & Janssens, 2009; Jans & Degraeve, 2007). This includes exact methods and approximation methods. More specifically, approximation methods or commonly known as heuristics are recognized as the dominant class of solution procedures (Barros *et al.*, 2021).

A summary of optimization methods employed to solve CLSP is presented in Figure 3.

Exact methods

Exact methods to solve the CLSP have been intensively studied as a branch of optimization algorithms (Doumari *et al.*, 2021). Integer programming methods, such as the Stadtler (1996) formulation of Mixed Integer Linear Programming (MILP), or the Dantzig-Wolfe (1960) decomposition, use mathematical optimization techniques to find optimal lot sizes while considering various constraints and objectives. While these methods are more flexible and comprehensive, they may be complex and computationally demanding.

Approximation Algorithm

Deterministic lot-size heuristics aim to offer approximate solutions without relying on dynamic programming or other precise algorithms, as demonstrated by Silver and Meal (1973) and Silver (1981). The existing research focuses on production lot-size methods for scenarios where demand is uncertain. These methods involve using deterministic lot-size outcomes and applying them to estimated mean demand, also known as forecasts, in order to determine the optimal timing and quantity for production. The management of uncertainty in the demand process involves the incorporation of buffer stock into the production quantities, as discussed by Silver (1981). Multiple studies have indicated that the variations in performance between different lot-size techniques become less significant as uncertainty levels rise (Wemmerlöv, 1989).

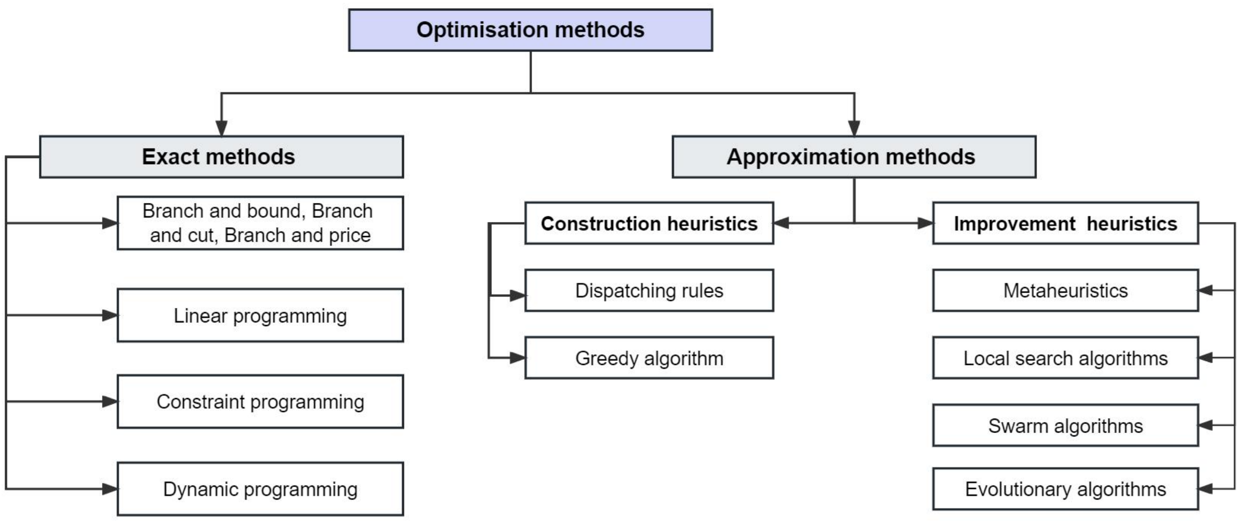


Figure 3 Classical optimisation methods and categorisation of algorithms

(Source: Kalata, 2021)

When faced with complex problems that require consideration of multiple factors, it is advisable to explore alternative methods. The use of simulation is frequently suggested by researchers due to the challenges associated with representing the intricate and frequently non-linear connections between process parameters and their economic effectiveness through mathematical equations (Milewski & Wiśniewski, 2022).

Simulation optimization, also known as optimization via simulation or simulation-based optimization, is a process that aims to improve the performance of simulated systems (Mulya, 2020). It involves identifying decision variables that will result in optimal system performance and assessing this performance through a simulation of the system. In addition, a simulation is a valuable tool in situations where demand and lead time exhibit probabilistic behaviour, as highlighted by Render *et al.* (2016).

The topic of using simulation for inventory analysis holds significant importance in the literature on simulation. Simulation is utilized to enhance the efficiency of system parameters, specifically reorder points and order-up-to levels within an inventory system. The study conducted by Liu *et al.* (2013) and Zhang *et al.* (2014) involved the development of a spreadsheet model. This model aimed to integrate a simulation of the ordering process within a national pharmacy supply chain. Additionally, the researchers implemented an iterative procedure to identify solutions that were close to optimal. Both companies utilize a periodic review reorder point (s) and order-up-to-level (S) policy to effectively manage their inventory. However, the models did not consider constraints related to warehouse capacity.

Spreadsheets are widely recognized as a valuable tool for both academia and practitioners in the field of operations research (Attar *et al.,* 2016). This is primarily due to their ability to provide an efficient and visually appealing platform for developing models. The widespread use of these methods can be attributed to their effectiveness in areas such as demand forecasting, resource optimization, simulation, and inventory management. The field of inventory management has seen a proliferation of spreadsheet models over the years. However, the majority of these models primarily utilize embedded statistical functions like NORMDIST and NORMSINV to calculate complex inventory formulas (Chopra & Meindl, 2012). In their study, Attar *et al.* (2016) proposed a continuous-review base-stock inventory model that incorporates lost sales. This model is designed to address the inventory needs of general compounds and account for the variability in lead times. A hybrid simulation-optimization strategy has been developed to effectively address these generalized situations. The inclusion of a cost function and mathematical models in the simulation model allows for a practical and effective method of determining the best possible settings, even when faced with real-world limitations and uncertainties.

2.4 Treatment of Uncertainty

Addressing demand uncertainty is crucial in order to avoid stock-outs. Uncertainty can be addressed through the utilization of either a stochastic programming framework or the incorporation of a safety stock. Stochastic inventory optimization problems remain highly complex in terms of both modelling and solution. Therefore, their ability to handle larger problem sizes is restricted. Various authors have conducted research on the safety stock problem and have presented inventory models that account for various types of uncertainty and risks, employing diverse methodologies (Barros *et al.*, 2021).

Accurate demand forecasting is crucial in supply chain management to avoid inventory shortages or surpluses, low service levels, rush orders, inefficient resource utilization, and the propagation of the bull-whip effect (Ho, 2018; Choi *et al.*, 2017). Strategies for managing demand uncertainty include component commonality, risk pooling, safety stock, safety lead time (Hong *et al.*, 2018), flexible supply contracts, subcontracting/outsourcing, and postponement (Barros *et al.*, 2021). Gupta and Maranas (2003) proposed that enterprises have two strategic options when confronted with uncertain demand. An entity has the option to adopt either a “shaper” or an “adapter” strategy in order to address uncertainty. The company's objective in the former was to reorganize the distribution of demand, thus minimizing potential losses and maintaining potential gains. This is commonly accomplished by entering into contractual agreements with the customer. The company may provide a supply contract to its customer, offering a price discount in exchange for a minimum/maximum quantity commitment (Anupindi & Bassok, 1999). In contrast, Gupta and Maranas (2003) indicated that the adapter strategy does not seek to influence market uncertainty. This means that the company manages the risk associated with its assets, such as inventory levels and profit margins, by continuously adjusting its operations in response to changing demand patterns.

Price uncertainty refers to the variability in the selling price of materials or raw materials by suppliers, which is caused by market price fluctuations or discount campaigns (Hong *et al.*, 2018). Pricing is a crucial consideration in the procurement process due to its impact on both logistics total cost and operational decisions (Choi *et al.*, 2017). Several additional papers have examined the optimal inventory policy in the context of price uncertainty, although only a limited number of them are mentioned in this section. Zipkin (1989) examined an inventory system that experiences periodic fluctuations in both demand and input price. This leads to a tendency for the firm to increase its inventory level when the price is low. Houtum *et al.* (2003) considered the optimal strategy of dual sourcing, involving a regular supplier and a spot market. Angkiriwang *et al.* (2014) suggest that flexible contracts and price risk hedging are viable strategies for managing price uncertainty. According to Reina *et al.* (2014), flexible contracts and price risk hedging are two strategies that can be employed to address the issue of price uncertainty. In their study, Liang *et al.* (2012) examined an option contract and demonstrated the existence of a viable price range that resulted in profitability for both the buyer and the supplier.

2.5 Summary

Inventory's role as a buffer against uncertainty has been widely acknowledged in the field of inventory management. Maintaining a balance is essential as excessive inventory can offset increasing operational profits. Inventory management is heavily reliant on lead time, which refers to the time it takes for an order to be placed and received. Longer lead times necessitate maintaining larger inventory levels. This emphasizes the critical importance of dependable suppliers in supporting effective supply chain operations.

Lot size strategies, such as the Wagner-Whitin algorithm, aid in determining optimal manufacturing quantities and timing to minimize costs. Although this technique yields optimal solutions, its computational cost, particularly in terms of required memory, can pose practical challenges. The Capacitated Lot Sizing Problem, an extension of the Wagner-Whitin problem, is known to be an NP-hard optimization problem. While dynamic programming can provide explicit solutions, its application to large instances may become infeasible. Exponential temporal and spatial complexity poses limitations on scalability.

These approaches are particularly valuable in situations where demand fluctuates over time, such as when it is influenced by factors like the day of the week or the month.

Simulation is widely used in inventory systems to optimize system parameters, particularly in stochastic environments. It is particularly valuable in determining reorder points and order-up-to levels. This chapter presents an introduction to a popular strategy for solving inventory problems, particularly CLSP, emphasizing its multiple characters, obstacles, and the various methodologies used to improve its efficiency.

Finally, there is also interesting research regarding the impact on inventory management and costs in general of risk hedging.

Chapter 3 Research Methodology

This chapter presents a comprehensive review of the techniques and methodologies utilized in the modelling and simulation of the consumables inventory model for Swanage Railway. The data collecting and processing techniques are also described.

Figure 4 below illustrates a holistic view of the research approach.

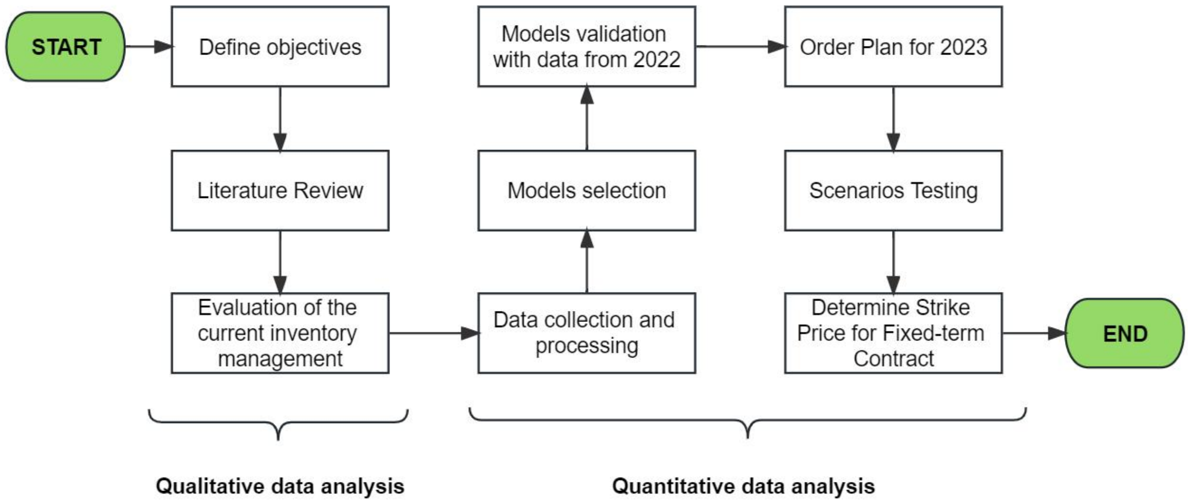


Figure 4 Research process

3.1 Brief Analysis on Current Inventory Control Practices

At regular time intervals, the staff who is in charge of ordering the consumable products assesses the current inventory level (stock on hand) of a specific product for the purpose of placing orders. Based on the available information, he makes a decision regarding the procurement of additional inventory from a supplier. The manager aims to reduce inventory holding and ordering costs within the decision-making time-frame, while also considering storage capacity.

The company employs a policy that sets both a minimum and maximum threshold to effectively manage its entire inventory. The company's strategy involves using historical data and the staff’s experience to predict and set a range for their inventory levels, with a minimum and maximum threshold. Swanage Railway implements an ordering process for new items when the stock level drops below a predetermined minimum threshold. The quantity of items ordered varies, however, it still follows a requirement for order size. The purpose of this order is to restock the inventory in order to achieve a predetermined maximum level.

The company's failure to account for set-up costs is an important oversight that this study aims to address. Set-up costs include many aspects of labour and resources required to enable the effective movement and storage of coal. This comprises employee time and effort spent transferring coal into storage, managing the arrival of coal-laden trucks, coordinating truck unloading procedures, and preparing the storage facility for coal arrival.

Holding cost can be interpreted as the cost of having capital tied up in inventory. This model is developed on the general formula for the unit holding cost h (Silver *et al.,* 1998):

$$h = \alpha v + f$$

Where: v represents the money invested when placing a unit of product in stock

f is the variable out-of-pocket cost for keeping one unit of product in stock for one year

α is the opportunity cost of capital of the firm (per year)

The company does not incur out-of-pocket storage fees because it has used the same coal storage facilities since the 1970s. Because of their unique location, these storage facilities are necessary for storing and supplying coal to the on-site steam engines. As a result, the project sponsor believes that the out-of-pocket cost in this situation should be £0.

The characteristics of the inventory management factors in Swanage Railway are summarized in Table 2.

Table 2. Summary of the problem in Swanage Railway's inventory system

	Coal	Diesel	Oil
Unit price range	Large variability Follow international market's fluctuations	Stable Follow the supplier's quotation	Stable Follow the supplier's quotation
Setup cost	£10 per order		
Holding cost	Interest rate per year: α = 7% multiplied by average unit cost		
Demand	Follow timetable allocation but with peak days, strong seasonality and large variability	Fairly stable	Fairly stable
Lead-time	About 1 week	About 1 week	About 1 week
Minimum order quantity	One full truckload (about 28 tons)	1000 gallons	105 litres
Storage capacity on site	Limited to 52 tons	15000 gallons	1500 litres
Storage capacity on a locomotive	2 tons	none	none

3.2 Data Collection and Preprocessing.

Qualitative data were obtained from relevant scientific papers and articles obtained from online databases. Information was also collected through discussions and consultations with experts from Swanage Railway.

Regarding the **quantitative data** provided by the company, this has been previously gathered and stored in their databases over the past two years (2021 and 2022). After consultation with the project supervisor, the data for the year 2022 is selected to investigate the ordering practices, considering that the timetable in the years 2023 and

2024 is under research and deemed to replicate 2022's allocation. The information will be processed using various methods to create coherent structures for future utilization.

One potential task involves performing data mining on the company's main software to extract valuable data sets that can be utilized in the project. The process will be executed by the supervisors at Swanage Railway.

After extracting the information, an additional method to be employed is the manual examination of the data contained in the Excel files. The primary objective of this second approach is to identify and rectify errors, as well as account for any potential missing data.

Cost-related data were collected through personal consultations with experts at Swanage Railway. Raw data collected from these databases were treated to extract the information that is used in the models. Because information about the company and its activities was in its early stages, a significant amount of time was spent learning the situation and how its operations functioned. This data was collected through discussion with the industry supervisor and numerical data obtained from the system.

3.3 Price and Demand Parameter

According to Abuizam (2011), the design of any spreadsheet simulation model requires the inclusion of three fundamental aspects. To begin, managers must have a systematic approach for inputting random quantities from specified probability distributions. At least one input variable cell containing random numbers is recommended for creating a full simulation model. Secondly, the developer must ensure that the right Excel formulas are used to build a relationship between the output cells and the input values. Thirdly, it is necessary that the developed spreadsheet can be recalculated several times and the subsequent outputs for quantitative analysis are gathered properly.

3.3.1 Demand Input

Accurate demand forecasting is critical for properly optimizing inventory levels (Tadayonrad & Ndiaye, 2023). However, in practical situations, demand is rarely precisely predicted or remains constant. According to Dillon *et al.* (2017), as the number of uncertainty levels increases, so does the complexity of these demand calculations.

Given that the company does not typically record daily demand for consumables, collecting historical data to do conventional validation was not viable. The demand calculation is then built with the following assumptions:

- A simplified demand model could be sufficient to gain insights.
- Future demand could be modelled based on historical demand, factoring in the timetable schedule. These timetable scheduling – designed with colour code – are assumed to be available before determining the demand input.

Appendix I provides a summary of the input cell in the demand sheet.

Demand input data sheet generating process

This demand modelling process could be used to create demand data for all consumables inventory and integrate it with timetable input. The last required input file for simulation, capacities, had to be created manually. However, since both steam and diesel locomotives' numbers and capacities will not change drastically over time, in this specific problem, the identical historical timetable could be re-used and modified in the future for a more realistic simulation. For every period in the demand dataset:

Step 1: For every consumable product in the purchasing portfolio, retrieve the corresponding steam factor and diesel factor, following this timetable allocation (Table 3).

Table 3 Steam and diesel locomotives allocation (Unit: Locomotives)

Time table	Blue	Green	Red	Purple	Yellow
Steam	1	1	1	1	2
Diesel	0	1	1	2	0

Step 2: Draw a sample from a normal distribution

To calculate the statistical parameters for demand input, this dissertation is based on the rules proposed by Brase and Brase (2015, p. 311). They report that "for a symmetrical and bell-shaped distribution, approximately 95% of the data lies within two standard deviations of the mean". This is considered a commonly used approach for representing 'commonly occurring' data values, which means a 95% range of data extends from $\mu-2\sigma$ to $\mu+2\sigma$ (Schumm *et al.*, 2016). Hence, the length of this range is equivalent to four times the standard deviation (4σ). In the same vein, Fleissig (2014) stated that "the standard deviation for a normal distribution can be estimated by dividing the range by four" (p. 46).

The computational steps are reported in detail in Appendix I. Table 4 reports the statistical parameter for consumables demand.

Table 4. Input parameter for consumables demand

Item	Unit	Mean (μ)	Standard deviation (σ)
Warming fire coal	Ton	0.3	0.045
Steam raising fire	Ton	0.75	0.1125
Coal for 5 round trip	Ton	1.5	0.225
Diesel for 1 round trip	Gallons	12.2	0.915
Steam oil 220	Litre	1	0.025
Bearing oil	Litre	6	0.15

Step 3: Determine the Warming factor using the If function in Excel: The overnight warming up period only applies if the locomotive has not been used the previous day. Then multiply the demand distribution with the corresponding factor.

Step 4: Compute the daily coal demand for everyday under this formula:

> **Daily coal demand =** *Number of steam locomotive * Coal demand for 5 round trip + Warming fire factor * Coal demand for Warming fire + Coal demand for Steam raising fire*

The challenges in accurately forecasting demand can be attributed to the complexity and unpredictability of demand patterns, particularly due to the presence of distinct high and low seasons. The demand and price of coal are characterized by a higher level of uncertainty when compared to diesel and oil, which have fixed prices in quotations. Hence, a validation process is carried out to analyse how the model behaves when it adapts to these changes by considering various scenarios (see Section 4.4).

3.3.2 Consumables Price Input

It can be observed from Figure 5 that the total cost spent for purchasing coal outnumbered other consumables categories. Therefore, we focus wholly on investigating the coal order practices Moreover, the purchasing staff emphasized that coal price follows the international market fluctuation, which means it is characterized by a higher level of uncertainty when compared to diesel and oil, which have fixed prices in quotations.

Data is collected from the World Bank's report on Australian Thermal Coal data (IndexMundi, 2023), recorded every month. The forecast is developed on a monthly basis following the company's supplier contract terms.

Input for coal price (see Appendix II) is a forecasting model developed in Excel, showing the base forecast with upper bound and lower bound values with a confidence interval equal to 95% (Figure 6). This means there is 95% that the price will fall into the range between upper bound and lower bound value. The Excel implementation of exponential smoothing forecasting is founded on the AAA alternative, which encompasses additive error, additive trend, and additive seasonality components of the Exponential Triple Smoothing (ETS) method (Cheusheva, 2023). This technique effectively mitigates small variations in historical data trends by identifying patterns of seasonality and establishing confidence intervals.

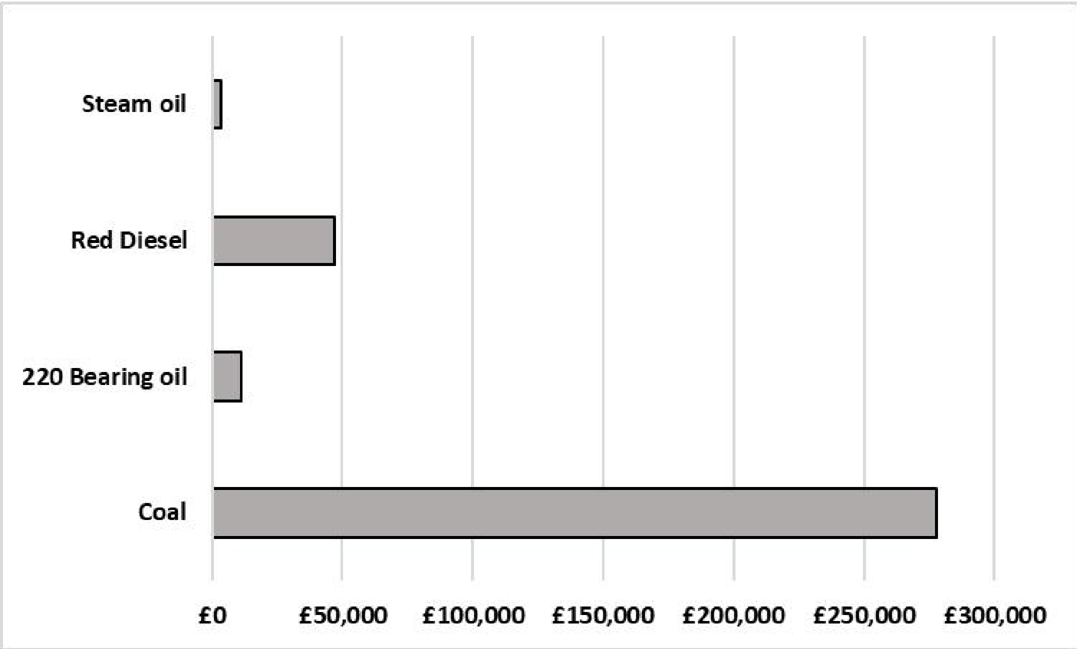


Figure 5 Swanage Railway's Consumables Purchasing Cost (Unit: Pound Sterling)

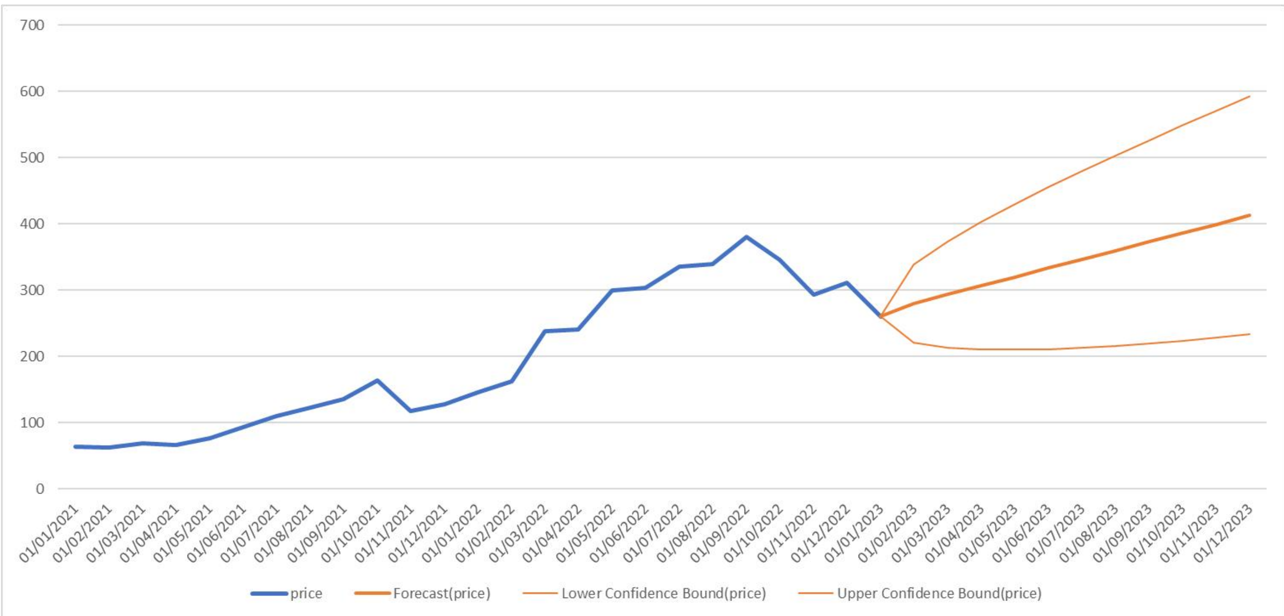


Figure 6 Australian Thermal Coal Monthly price forecasting chart - Pound Sterling per Metric Ton

3.4 Inventory Model Formulation

Table 5 summarizes the parameter denotations and the decision variables that will be considered in the following implementation.

Table 5 Summary of the Inventory Model's parameters and decision variables

Group	Denotation	Meaning
Indexes	i	item; $i = 1, 2, \ldots, N$
	t	period ; $t = 1, 2, \ldots, T$
Parameters	T	Number of periods (days) in the planning horizon.
	N	Number of products in Swanage Railway's purchasing portfolio.
	d_{it}	Demand for product i in period t. Demand in each period t is non-negative, independent, and deterministic with known statistical distribution
	BS_i	Order size for product i (e.g., coal ordered in 28-ton lorries).
	A_i	Setup cost for replenishing product i in a period This model set this value to be 10 pound per order
	W	Storage capacity constraint for the warehouse.
	h_{it}	Total holding cost if the entire demand for product i in period t is replenished in period t.
	P_{it}	Price of product i in period t.
Variables	x_{it}	Number of units of product i ordered in period t.
	I_{it}	Number of units of product i kept in inventory in period t.
	u_{it}	Binary variable indicating whether an order is placed for product i in period t (u_{it} =1 if an order is placed in that period, u_{it} = 0 otherwise).

Assumptions

The problem is first modelled as a deterministic single-product inventory model. At the moment in the above model there is nothing that connects one consumable to the other consumable, so we can separate the model into N single-product models.

Shortage and back-orders are not permitted.

This model assumes that there is no discount for large orders.

Each replenishment for a product at the beginning of a period is associated with a Setup cost S_i.

Replenishment lead times are assumed to be 1 week. Ordered products in period t will lead to inventory in period $t + 7$.

The storage capacity C_i for each product is assumed to be constant over the planning horizon.

Decision variables

The model has three distinct groups of decision variables.

x_{it} : Number of units of product i ordered in period t.

$$i = 1, 2, \ldots, N \, ; \; t = 1, 2, \ldots, T$$

I_{it} : Number of units of product i kept in inventory in period t.

$$i = 1, 2, \ldots, N \, ; \; t = 1, 2, \ldots, T$$

u_{it} : Binary variable indicating whether an order is placed for product i in period t (u_{it} =1 if an order is placed in that period, u_{it} = 0 otherwise).

$$i = 1, 2, \ldots, N \, ; \; t = 1, 2, \ldots, T$$

Objective function

Minimize Total cost = Purchasing cost + Set up cost + Holding cost

Minimize

$$Z = \sum_{i=1}^{N} \sum_{t=1}^{T} (P_i x_{it} + S_i u_{it} + h_{it} I_{it}) \; ; \; i = 1, 2, \ldots, N \, ; \; t = 1, 2, \ldots, T$$

Constraints

Demand constraint: Ensure that the demand for each product is satisfied in each period:

$$I_{it} + x_{it} = d_{it}\; i \;=\; 1, 2, \ldots, N\;;\; t \;=\; 1, 2, \ldots, T$$

Constraints to define inventory balance in each month.

$$I_{i(t+1)} \;=\; I_{it} + x_{it} - d_{it} \quad i \;=\; 1, 2, \ldots, N\;;\; t \;=\; 1, 2, \ldots, T$$

The inventory position, IP is evaluated at each new period. Equation gives the inventory position.

$$IP_i = \; I_i + OR_i$$

where is the physical inventory in stock, OR_i is the orders released but not yet received

Replenishment lead time constraint ensuring that the orders placed in period t are delivered in period t + 7:

$$\sum_{t'=t+1}^{t+7} x_{it'} \geq \; d_{it}\;;\; i \;=\; 1, 2, \ldots, N\;;\; t \;=\; 1, 2, \ldots, T$$

Storage Capacity constraints.

$$\sum_{i=1}^{N} I_{it} \leqq \; C_i\;;\; i \;=\; 1, 2, \ldots, N\;;\; t \;=\; 1, 2, \ldots, T$$

Non-negativity of the production and inventory quantities.

$$x_{it}, I_{it} \;\geqq\; 0;\; i \;=\; 1, 2, \ldots, N\;;\; t \;=\; 1, 2, \ldots, T$$

$$u_{it} \in \{0,1\};\; i \;=\; 1, 2, \ldots, N\;;\; t \;=\; 1, 2, \ldots, T$$

Order size constraint: Ensure that the ordered quantity for coal (product i) is a multiple of the order size:

$$x_{it} = BS_i \cdot u_{it};\; i \;=\; 1, 2, \ldots, N\;;\; t \;=\; 1, 2, \ldots, T$$

3.5 Simulation-optimization Spreadsheet Design (Sim-Opt)

The process simulation section with relevant formula is summarized in Table 6.

Table 6 Summary of data in simulation section

Column	Name	Function	Method
C	Price per unit	Section 3.3.2	
D	Demand input	Section 3.3.1	
E	Days of Week	Determines review period	The review periods for this case occur on Mondays and Fridays
F	Ordering Period	Indicates whether it is a review period or not	1 indicates review period, 0 indicates otherwise, input 1 for Monday or Friday
G	Beginning Inventory	Displays current inventory on hand	Equal to previous period ending inventory
H	Inv Position	Shows where the inventory is placed	Inventory position = On-order inventory + Inventory level
I	Order Or Not	Indicates whether to order or not	1 for ordering 0 for not ordering
J	Order Quantity	Displays the quantity of order	Rounded to the nearest multiple of the package size
K	Order Arrival	Displays the arrival date and quantity of order	Calculated according to the lead time of the consumables inventory
L	Ending Inventory	Displays Ending inventory	= beginning inventory - Demand in the period + order arrival
M	Out Of Stock	Calculate the total period with out of stock happening	= 1 if demand in that period is greater than ending inventory

This model is built on a periodic review reorder point (s) and order-up-to-level (S) policy to manage the company's inventory. The company will place an order to increase a consumable's inventory to an order-up-to level (S). If inventory exceeds the reorder point (s), the company will wait until the following review period. Because coal is delivered in 28-ton lorries, each order quantity is rounded up to represent a multiple of the order size.

The problem involves two variables, s and S, which are positive floating point numbers. Barati (2013) demonstrates that the Evolutionary solver utilizes random sampling as a component of its methodology. This characteristic classifies it as a stochastic method, as it has the potential to produce varying solutions across different iterations. After running the initial implementation of the simulation model with the Evolutionary option in Excel Solver, it was noticed that the initial solution greatly impacts the convergence and quality of the final solution obtained (Kumar & Mageshvaran, 2020). The formula for initial solution is built based on the famous EOQ and Reorder point concept.

The formula (1) for calculating the EOQ is adopted from Harris (1913):

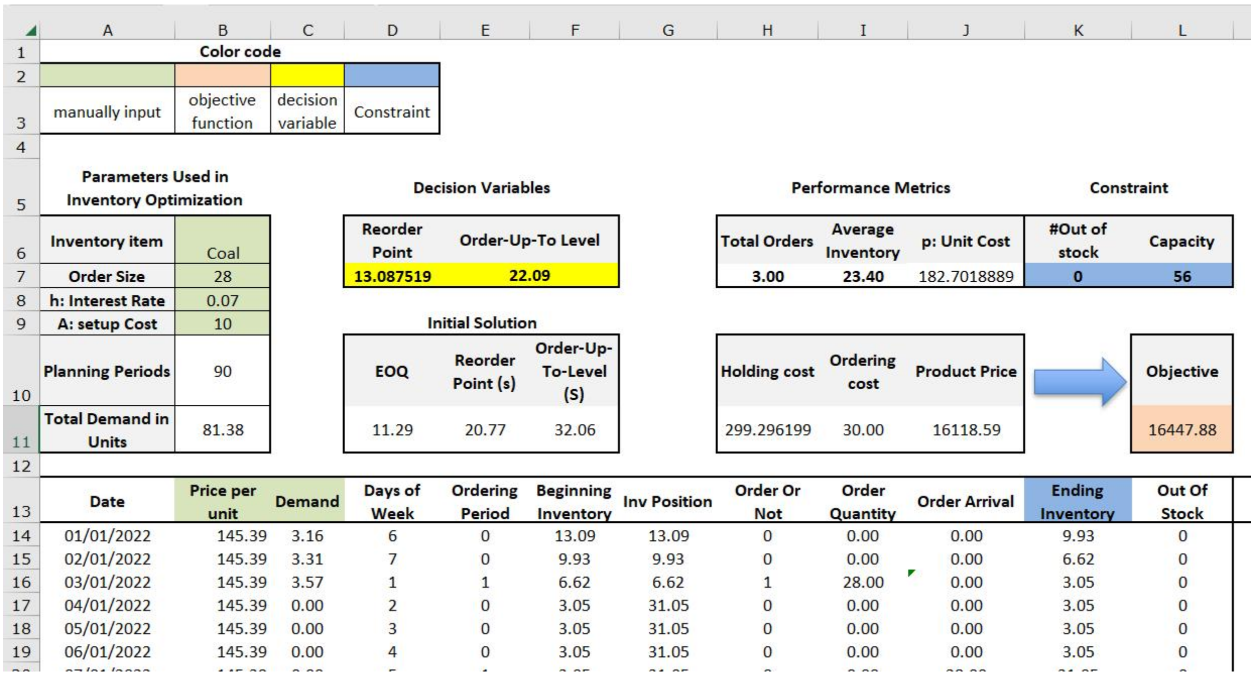
$$EOQ = \sqrt{\frac{2 \times Total\ Demand \times Ordering\ Cost}{Holding\ Cost\ Per\ Unit}} = \sqrt{\frac{2\ \times\ Total\ Demand \times Ordering\ Cost}{Interest\ rate\ \times Unit\ Cost}} \quad (1)$$

$$Reorder\ point\ (s)\ =\ Maximum\ daily\ demand * Average\ Leadtime\ \ (2)$$

$$Order - up - to\ level\ (S)\ =\ EOQ\ +\ Reorder\ point\ \ (3)$$

In the formulation of (2), instead of adopting a common approach, the reorder point (s) is calculated by multiplying the maximum daily demand by the average lead time. After conducting the demand data processing step, the author noticed that the consumable demand pattern is intermittent with a large number of periods recorded zero demand. In other circumstances when data on lead-time demand standard deviation is available, the reorder point can be determined with any analytical approximation solutions.

A thorough description of the “move and adjust” heuristic adopted in finding these two decision variables is provided in Appendix III. This Pseudocode is an upgraded version of Liu *et al.* (2013) and Zhang *et al.* (2014), accounting for capacity constraints and elimination of stock-out situation.



	A	B	C	D	E	F	G	H	I	J	K	L
1		Color code										
2												
3	manually input	objective function	decision variable	Constraint								
4												
5	Parameters Used in Inventory Optimization				Decision Variables				Performance Metrics		Constraint	
6	Inventory item	Coal		Reorder Point	Order-Up-To Level			Total Orders	Average Inventory	p: Unit Cost	#Out of stock	Capacity
7	Order Size	28		13.087519	22.09			3.00	23.40	182.7018889	0	56
8	h: Interest Rate	0.07										
9	A: setup Cost	10			Initial Solution							
10	Planning Periods	90		EOQ	Reorder Point (s)	Order-Up-To-Level (S)		Holding cost	Ordering cost	Product Price		Objective
11	Total Demand in Units	81.38		11.29	20.77	32.06		299.296199	30.00	16118.59		16447.88
12												
13	Date	Price per unit	Demand	Days of Week	Ordering Period	Beginning Inventory	Inv Position	Order Or Not	Order Quantity	Order Arrival	Ending Inventory	Out Of Stock
14	01/01/2022	145.39	3.16	6	0	13.09	13.09	0	0.00	0.00	9.93	0
15	02/01/2022	145.39	3.31	7	0	9.93	9.93	0	0.00	0.00	6.62	0
16	03/01/2022	145.39	3.57	1	1	6.62	6.62	1	28.00	0.00	3.05	0
17	04/01/2022	145.39	0.00	2	0	3.05	31.05	0	0.00	0.00	3.05	0
18	05/01/2022	145.39	0.00	3	0	3.05	31.05	0	0.00	0.00	3.05	0
19	06/01/2022	145.39	0.00	4	0	3.05	31.05	0	0.00	0.00	3.05	0

Figure 7 Excel interface of the Simulation spreadsheet

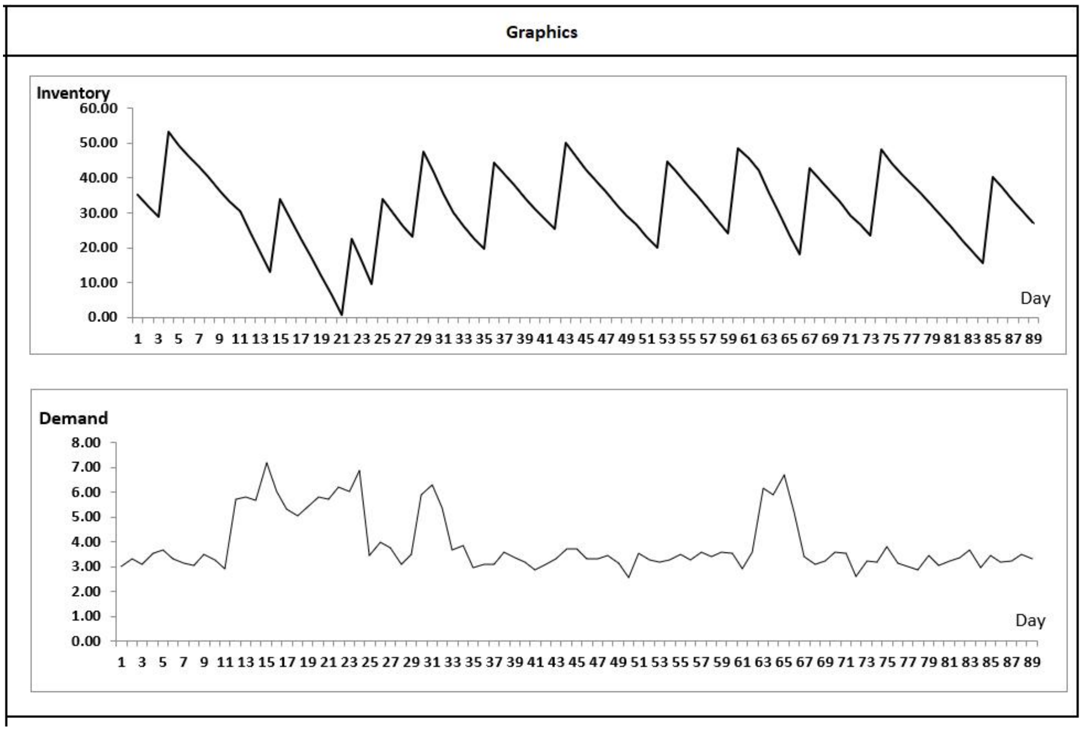


Figure 8 Examples of Inventory and Demand Graphics incorporated in the Simulation spreadsheet

The first model also provides an interactive platform for the managers to have an ordering plan which specifies on which day they should place the order, and visualization tools for ending inventory (Figure 7) and demand figures (Figure 8).

Additionally, it was observed that Excel Solver struggles to handle larger instances of the problem efficiently, as the computational time increases significantly. Therefore, a Dynamic Programming model with Warehouse capacity is implemented to solve a long-term capacitated lot sizing problem.

3.6 Dynamic Programming Model with Warehouse Capacity (Dynamic Model)

For a one-year planning period, the model provided in the previous section needs to check for every period's ending inventory for capacity constraints, which yields 365 constraints for Excel Solver. This is significantly more than Excel Solver can handle (the normal built-in MS Excel Solver has a limit of 200 variables).

We thus developed another approach based on a Dynamic Programming model with warehouse capacity. This model was originally developed by Beullens (2023) for the time-dependent demand uncapacitated standard inventory model. This model has been modified to include Swanage-specific characteristics:

- ❖ Zero or near-zero set-up costs: All costs are expressed on a per ton basis for the delivered consumable. It can be argued that Swanage Railway incurs a fixed order cost due to the amount of time and labour required to process an order.
- ❖ Maximum order size: For coal, for example, the ordering process typically restricts the order size to a full truckload of 28 tonnes.
- ❖ Minimum order size: In absence of set-up costs, models would suggest to order every day what is needed. In reality this may not be acceptable. By setting the minimum order size slightly below the maximum order size, the algorithm can effectively place orders without excessively accumulating surplus inventory.
- ❖ Maximum storage capacity: The Swanage Railway has a coal storage capacity of approximately 52 tons, with the potential to accommodate a few additional tons for each operational steam locomotive.

The first part of the code sets up the necessary data and parameters for the optimization process (Figure 9). It extracts essential information, such as the forecasted demand, pricing data, and cost-related parameters, from the "Swanage Data" worksheet. These values serve as the foundation for the subsequent calculations.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	SWANAGE CONSUMABLES: OPTIMAL ORDERING AND STRIKE PRICE FOR COAL												
2	number of days (planning horizon)		365		Maximum order size			28	ton				
3	set-up cost (£/order)		10		Maximum storage capacity			56	ton	Map Swanage Data to Data Worksheet			
4	revenue per ton (estimate or dummy, £/ton)		500		Minimum order size			26	ton				
5													
6	ID	Date	Price per unit(£/ton)	Demand (ton/day)	Days of Week								
7		01/01/2023	260.26	3.66	7								
8		02/01/2023	260.26	3.44	1								
9		03/01/2023	260.26	3.89	2								
10		04/01/2023	260.26	0.00	3								
11		05/01/2023	260.26	0.00	4								
12		06/01/2023	260.26	0.00	5								
13		07/01/2023	260.26	0.00	6								
14		08/01/2023	260.26	0.00	7								
15		09/01/2023	260.26	0.00	1								
16		10/01/2023	260.26	0.00	2								
17		11/01/2023	260.26	0.00	3								
18		12/01/2023	260.26	0.00	4								

Figure 9 "Swanage Data" worksheet - Input data for the Dynamic Programming

One of the critical features of this code is its ability to assess the optimal number of order cycles by iteratively applying Backward Dynamic Programming. The goal is to **find the optimal number of order cycles that minimizes the total cost, which includes ordering costs, setup costs, holding costs and other relevant expenses.** The benefit of the approach is that one can quickly get an idea of the total expected cost for consumables over a certain planning horizon, e.g. the next year, given a forecast of:

- Amounts of consumable needed for each day over a time horizon in the model. For coal, for example, this forecast could be based on the results of timetabling for the next year.
- The price per unit of consumable if ordered on a day. One can use forecasts of coal prices, for example, and break these down over the different months, weeks, days of the time horizon.

Based on tests conducted with Swanage data, a planning horizon of one year is solved in the range of seconds.

The second purpose of the code is an iterative loop that evaluates different price scenarios, moving from the highest to the lowest price. For each price scenario, it calculates the optimal order plan based on the Backward Dynamic Programming approach. The code maintains a record of the results for each price scenario, including the optimal number of order cycles and associated costs. This information is then used to determine **the strike price, which represents the price of a fixed-price contract over the same time horizon at which the company can achieve the same optimal lowest cost as for the case that the price is not fixed** (as given by the data in the “Swanage Data” worksheet). The company should thus aim to secure fixed-price contracts at or below the strike price. If no supplier can offer a contract with a fixed price lower than the strike price, Swanage Railway would not derive any advantage from such fixed price contracts, assuming that the forecasted price evolution, as indicated by the data in the "Swanage Data" worksheet, is accurate.

Further research would investigate how to add uncertainty in forecasts of demand and prices to help establish insight into their impact.

The strike price for a fixed-term contract is arrived at Cell D5 by evaluating a range of possible fixed prices that would apply over the whole planning horizon (see also Figure 10). This strike price must lie between the highest forecasted price and the lowest forecasted price. The code enters a loop that iterates over a range of possible fixed coal prices, starting from the highest price and decreasing incrementally to the lowest price (Figure 10).

Over the same planning horizon, what is the `strike price' for a fixed price contract of equal total cost (but with optimal adjusted order pattern)?

Aim to get a fixed term contract with a price at most the optimal strike price.

Strike Price		130.26	
Price (£/product)	Orders	Total Cost (£/planning horizon)	Relative Savings (£/planning horizon)
260.26	30	-206721.1694	-102356.1426
259.26	30	-205928.0349	-101563.0082
258.26	30	-205134.9005	-100769.8738
257.26	30	-204341.766	-99976.73932
256.26	30	-203548.6316	-99183.60488
255.26	30	-202755.4972	-98390.47044
254.26	30	-201962.3627	-97597.336
253.26	30	-201169.2283	-96804.20156
252.26	30	-200376.0938	-96011.06712
251.26	30	-199582.9594	-95217.93268
250.26	30	-198789.825	-94424.79824
249.26	30	-197996.6905	-93631.6638
248.26	30	-197203.5561	-92838.52936

Calculate Strike Price

Figure 10 "Strike Price"worksheet in Excel

For each price, the code performs the following steps as seen in Figure 11.

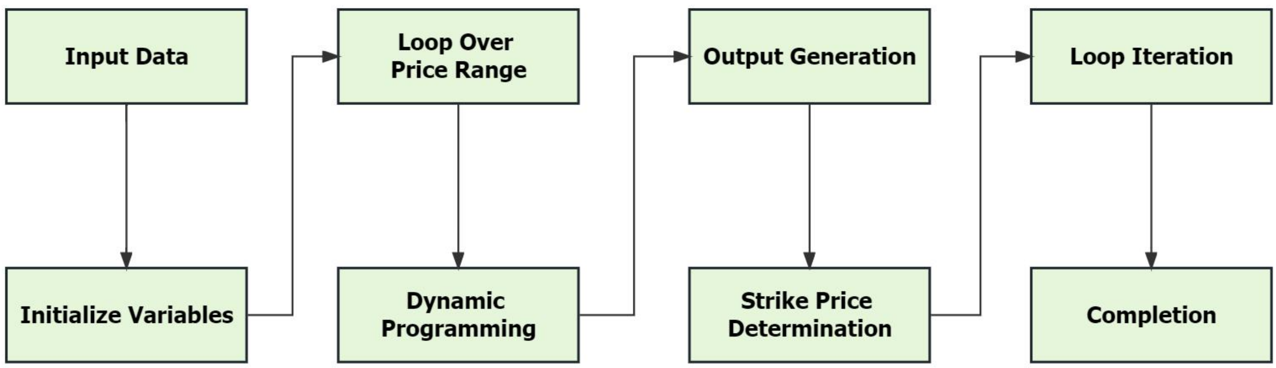


Figure 11 Order of the VBA code processing

3.7 Summary

We developed two distinct models using separate spreadsheets. The Sim-Opt model helps in determining optimal reorder points and order-up-to levels in situations where the forecasted demand per day is both time-dependent and uncertain. The methodology relies on simulation. The model's ability to examine uncertainty is limited to a time frame of approximately three months.

The second model analyzes optimal ordering cycles considering specific conditions of maximum and minimum order quantities, limited storage capacity, and near-zero fixed ordering costs, specifically tailored for Swanage Railway. The input for this model consists of time-dependent forecasts of daily demand and the corresponding price of the product over a specified time period. The algorithm utilizes Dynamic Programming. The model is capable of forecasting the total costs of consumables for instances lasting one year or more. Moreover, it can determine the strike price, providing valuable insights into the financial advantages of fixed-price contracts compared to spot-price orders.

The current Dynamic Programming model lacks the capability to incorporate uncertainty in the forecasted figures. Further research could be conducted to explore this topic. However, when using it as a tool to estimate costs over long periods of time, the lack of explicit modelling uncertainty appears to be not a significant limitation. Alternatively, the model can be rerun to generate forecasts for different scenarios (optimistic, neutral, pessimistic), which can aid in evaluating the financial consequences.

Chapter 4 Results and Analysis

4.1 Models Validation

The model was run using the data in 2022 first to investigate the differences between the past ordering practices and the models' results. Then the author compares the result of the two models provided in Table 7 and Table 8 with the real data of the company (Table 9) to comment on the suitability of the new model to simulate the real data.

Table 7 Sim-Opt Results For The Year Of 2022

Summary	Objective (TC)	Total order (O)
Spring season (1)	16753.14	3
Summer season (2)	88089.95	11
Autumn season (3)	115840.23	9
Winter season (4)	46002.86	6
Total	**266686.19**	**29**

Table 8 Dynamic Model Results

Summary	Objective (TC)	Total order (O)
Dynamic Model	266542.70	34

Table 9 Total cost related to the coal purchasing practice in 2022

Real data from order history	Product cost	Total coal ordered	Total order
Spring season (1)	20560.96	83.86	3
Summer season (2)	90599.8	280.1	10
Autumn season (3)	84199.52	230.4	9
Winter season (4)	77233.5	134.1	7
Total	272593.78	725.06	29

The initial results indicate that the margin of error in total cost incurred for Sim-Opt and Dynamic Model did not exceed 2% respectively. Therefore, it is valid to conduct scenarios testing and draw inferences from variations in the applied inputs.

4.2 Results Adopted From Sim-Opt

Table 10 displays the spreadsheet Sim-Opt model, which utilizes the Economic Order Quantity (EOQ) as the initial solution in order to achieve the optimal order quantity. After performing attempts on the initial solution, it was observed that no instances of stock-out occurred. Given the presence of capacity constraints, the order-up-to-level will be adjusted to address the issue of excessive inventory. As the EOQ model results in higher reorder point (s), it leads to overstocking, thus increasing holding costs. The simulation-optimization model reduces inventory costs. Refer to Appendix V for the complete comparison table.

A reduction in holding costs of 23.81% can be achieved (Table 10). The model proposes that increasing the frequency of orders can significantly reduce holding costs. One of the primary objectives of the models was to minimize the total cost while satisfying demand within lead time constraints. Through multiple iterations, the Excel Solver converged to optimal solutions that effectively balanced ordering costs and holding costs. The optimization process also considered capacity constraints, ensuring that production limits were not breached.

The Sim-Opt model provides a more accurate representation of the company's inventory management compared to the initial implementation of the simulation model using the Evolutionary option in Excel Solver. The extended model allows for a better understanding of the inventory system and provides a more comprehensive analysis of the total cost related to inventory management.

Table 10 Comparison between initial solution and optimal solution given by Sim-Opt model

Criteria	**Initial Solution**	**Improved Solution**
Setup cost	280	290
Holding cost	3522.02	2683.26
Total order	28	29
Total cost	267410.21	266675.16

4.3 Results Adopted From Dynamic Programming Model

Table 11 demonstrates the results for both a one-year time frame and a two-year time frame. The results were obtained using a basic demand forecast model, utilizing the same timetable input for the year 2022. The model also considered price fluctuations, which maintained an increasing trend.

Upon consultation with the industry supervisor, it has been observed that there is currently a train undergoing engine maintenance since 2019. As a result, there will be only one steam locomotive in operation within the next two years. The demand forecast is subsequently adjusted.

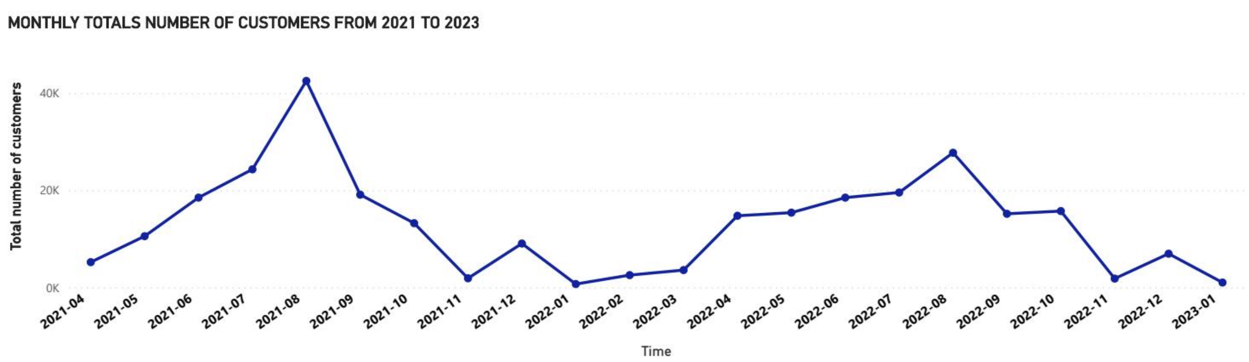
Table 11 Dynamic Programming Model Result

	One year plan	**Two year plan**
Total order	30	59
Average order cycle	11.74	12.15
Total cost	271079.61	662588.51

4.4 Scenarios Testing

4.4.1 Testing with seasonality of demand and price fluctuation

In the context of scenario testing, it is crucial to consider uncertain key data elements. This can be done by conducting sensitivity analyses, which help assess the potential impact of using different values for these elements. A fundamental aspect of sensitivity analysis involves examining a single variable and evaluating different values for that specific variable. In this process, it is important for the project sponsor to recognize the variations in benefits and net outcomes that arise when different levels of uncertainty level are taken into account. When faced with multiple uncertain variables, it is advisable to adopt a comprehensive scenarios testing approach. This approach entails conducting a broader range of sensitivity analyses, where several key input variables are adjusted simultaneously. The purpose of these analyses is to estimate the combined impact of these variables on total inventory cost.



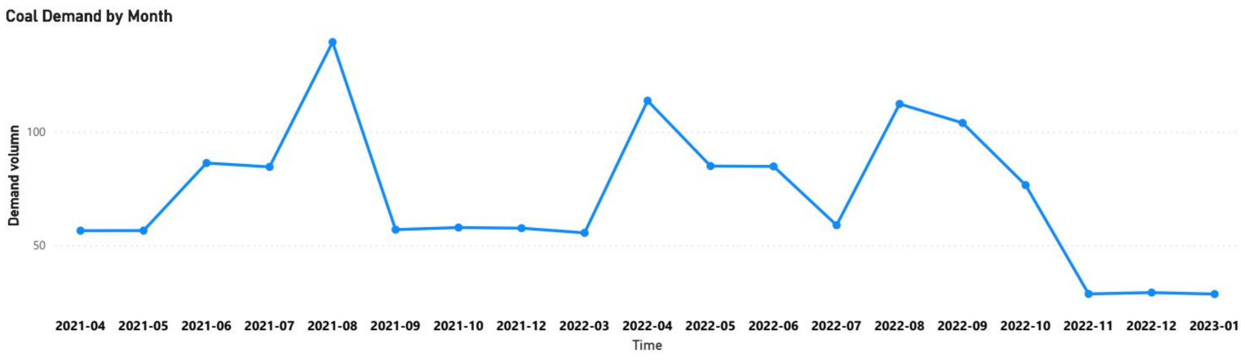


Figure 12 Customer number and Coal demand from April 2021 to January 2023

It is obvious from Figure 12 that the demand for coal seasonality aligns with the customer number trend. Therefore, the author divided the coal demand into 4 seasons to implement scenario testing.

The analysis focused on examining the impact of simultaneous changes in demand season and price forecasting on the parameters that characterize inventory control activity. Table 12 illustrates a combination of different case scenarios considering the fluctuation in demand and price.

Table 12. Scenarios matrix

Demand pattern, Price fluctuation	Low price(1)	Average price(2)	High price(3)
Spring season (1)	(1,1)	(1,2)	(1,3)
Summer season (2)	(2,1)	(2,2)	(2,3)
Autumn season (3)	(3,1)	(3,2)	(3,3)
Winter season (4)	(4,1)	(4,2)	(4,3)

The investigation consisted of a 3-month time of simulation for each scenario in coal inventory in relation to demand fluctuation (see Table 13). To ensure a balance across the scenarios, the same lead times and periodic review policy were included in all scenarios, allowing for a better comparison. To ensure that the constraint of "no stock-out" is met, the initial inventory levels were all set equal to the reorder point. The complete scenarios test results can be viewed in Appendix VI

Table 13 Reporting scenarios testing result

Demand pattern, Price fluctuation	**Low price(1)**	**Average price(2)**	**High price(3)**
Spring season	(1,1) s =11.52 S = 16.93 TC = 18797.97 O = 3	(1,2) s = 12.07 S = 17.44 TC = 23318.68 O = 3	(1,3) s = 13.09 S = 22.09 TC = 28596.11 O = 3
Summer season	(2,1) s = 20.83 S = 35.13 TC = 58846.49 O = 10	(2,2) s = 21.64 S = 22.73 TC = 90194.59 O = 10	(2,3) s = 24.35 S = 35.77 TC = 119274.35 O = 10
Autumn season	(3,1) s = 24.96 S = 36.12 TC = 61185.39 O = 10	(3,2) s = 22.08 S = 32.50 TC = 102196.87 O = 11	(3,3) s = 21.98 S = 31.18 TC = 140357.02 O = 10
Winter season	(4,1) s = 17.24 S = 35.96 TC = 32605.14 O = 6	(4,2) s = 17.92 S = 30.64 TC = 56495.29 O = 6	(4,3) s = 16.49 S = 23.31 TC = 79451.32 O = 5
Total cost and order for a year plan	TC = 171435.00 O = 29	TC = 272205.44 O = 30	TC = 367678.79 O = 28

The scenarios testing process shows that the same ordering pattern happens between 12 scenarios. The price fluctuation greatly impacts the total cost as it accounts for the largest percentage of the cost function. The limited capacity is one of the reason that the number of order remain unchanged.

4.4.2 Testing with the fluctuation of coal demand

The company currently has contracts with suppliers, but they cannot guarantee the quality of coal for each given order. Different coal origins and quality affect the coal consumption rate and thus the coal demand, yet the company is bound by the same pricing contract.

For example, coal is now imported from Kazakhstan. While it burns quickly and does not require too much time to start the engines, it is smoky, and the fire does not last long, so more coal is consumed. Thus, the models are still being tested with the volatility of coal demand, as coal quality might lead to a 30% rise in coal consumption, depending on the origin of the coal for that year.

Table 14 Testing with the fluctuation of coal demand using Dynamic Model

Demand pattern, Price fluctuation	Low price(1)	Average price(2)	High price(3)
Worst case scenario (demand +30%) (1)	(1,1) TC = 223127.3232 O = 39	(1,2) TC = 352205.6965 O = 39	(1,3) TC = 479806.1186 O = 39
Base case (2)	(2,1) TC = 172463.3244 O = 30	(2,2) TC = 271079.6133 O = 30	(2,3) TC = 366750.898 Or = 30
Best case scenario (demand -30%) (3)	(3,1) TC = 120757.7377 O= 21	(3,2) TC = 187727.2067 O= 21	(3,3) TC = 250864.3039 O = 20

The same pattern happens with the Dynamic Model performance as only the total cost greatly fluctuate while the total number of order remains unchanged, given the same amount of coal demand.

There is no difference in terms of ordering practice between the scenarios with the same demand characteristics. However, the total cost varies greatly due to the price fluctuation. In his study, Zipkin (1989) examines an inventory system that experiences periodic fluctuations in both demand and input price. The study finds that when the company anticipates an increase in price in the upcoming period, it tends to place larger orders in the current period, resulting in a higher inventory level. This situation can be confirmed in all Low-price scenarios where the order-up-to level is higher than that of the Higher price scenarios. It is noted that for the Higher price scenarios, the company is expected to have lower reorder-point and order-up-to level. This is because the increasing price leads to an increase in the holding cost (holding cost is collected by multiplying the interest rate with the unit cost). Lower level of inventory will help the company in saving holding cost.

4.5 Determination of the Strike Price for the Fixed-term Contract

The determination of the strike price for a fixed-term contract, as based on the Dynamic Model, involves a systematic and iterative process aimed at identifying the price at which a company can minimize its purchasing cost and, consequently, maximize cost savings. Table 15 presents the result for the strike price for each season and the strike price for the whole year if a long-term contract is applied.

Table 15 Strike price for a Fixed term contract (Unit: Pound Sterling)

Scenarios	Low price(1)	Average price(2)	High price(3)
Spring season	(1,1) 230.26	(1,2) 277.19	(1,3) 323.94
Summer season	(2,1) 210.06	(2,2) 318	(2,3) 426.25
Autumn season	(3,1) 215.2	(3,2) 358.8	(3,3) 500.39
Winter season	(4,1) 225.9	(4,2) 393.60	(4,3) 561.30
Strike price for a year plan	216.26	338.60	476.30

Chapter 5 Discussion

5.1 Implications and Recommendations

This project emphasizes the difficulty presented by the lack of documented real-time demand information, underscoring the necessity for enhanced processes in data collection and management to increase the precision of order planning. Moreover, the significance of the demand and price forecasting models in the optimization process cannot be underestimated, as mentioned before by (Hong *et al.*, 2018). Hence, it is recommended to engage in ongoing revision and enhancement of these models in order to maintain the reliability of the outcomes with respect to market dynamics.

The model can help streamline the order process by eliminating reactive ordering and reducing the risk of out-of-stock situations. Additionally, it incorporates coal price forecasting, which can assist the company in saving on ordering costs. By utilizing this model, the company can make more informed decisions and better adapt to dynamic supply chain scenarios. The prescribed policy from the Swanage Railway's inventory model may vary depending on different forecast measures and data characteristics. Companies can benefit from seeking a personalized policy for supply chain forecasting based on their unique environments, considering the variety of individuals and tasks involved. It is recommended that the Swanage Railway company pay attention to fluctuations in the coal market price and implement a more accurate forecasting model for coal prices.

According to Raj *et al.* (2022), when confronted with sudden price fluctuations, it is crucial for a company to adapt its pricing and procurement systems to be more flexible. In the current raw material market, annual contracts may not be a suitable choice due to high volatility. Merckx and Chaturvedi (2020) stated that adopting shorter terms such as quarterly or monthly contracts in a dynamic market and cost environment can enhance firms' ability to effectively evaluate and capitalize on price opportunities. The Dynamic Programming Model offers an efficient approach for calculating the strike price value, which can be quickly adapted to meet the needs of short-term or long-term contracts.

5.2 Comparison of the Models' Performance

The two models have their own strengths. The Dynamic Model with VBA code outperforms the Sim-Opt Model in Excel although the optimization heuristics in Excel Solver can output a closer to optimal point. Dynamic Programming reduces the complexity of solving a Capacitated Lot Sizing Problem and produces a long-term order plan for the company. Tests conducted using Swanage Railway's data have shown that planning horizons of one or two-year planning horizon can be solved within seconds, using the VBA code.

For the simulation model, managers can have an interactive platform to track current inventory status or test different order patterns by simply changing the periodic review interval with Excel functions.

5.3 Model Reuse

Access to more historical data allows managers to modify the approximation of probability distributions for both demand and lead time. The simulation spreadsheet enables managers to determine the optimal values of (s, S) without the need to manually select trial values. In certain cases, the trial values may deviate significantly from the optimal solution. The same process can be applied to create an ordering plan for other consumable products such as Oil and Diesel, by inputting data from Appendix II.

Finally, the proposed model exhibits a level of simplicity and user-friendliness that enables its utilization by staff members who may not possess advanced mathematical or computational proficiencies. The ease with which duplication and reuse can be achieved encourages a wider adoption, enabling firms to effectively monitor and automate their procurement operations, hence enhancing overall operational efficiency.

Developing a modified model may require similar skills and time as creating a new model. Additionally, a thorough understanding of the original model's methodology is necessary. From the perspective of the modeller, existing models can provide valuable inspiration, information, and technical insight. The utilization of Kroger's Simulation and Optimization (Zhang *et al.*, 2014) and Dynamic Programming Model (Beullens, 2023) approach and expertise enabled the efficient development of the Swanage model in a dedicated time-frame of three months.

In the future, it is suggested that the company modify the model with updated data including short-term forecasting of price. The scenario testing results highlight that dynamic pricing significantly affects inventory management. The study confirms that fluctuations in product prices create substantial uncertainty in the inventory equation. Failure to address this uncertainty can result in suboptimal inventory decisions, which can ultimately impact a company's profitability.

Chapter 6 Conclusion

6.1 Summary of Findings

This study investigates the inventory control practices employed by Swanage Railway. The company currently employs a policy that establishes minimum and maximum thresholds for inventory levels based on historical data and past performance.

The study employed diverse methods to process and organize the data for future applications. A simplified demand model may provide adequate insights, and future demand can be predicted by incorporating historical demand and considering timetable scheduling. The study aims to address the company's failure to account for set-up costs, which include labour and resources required for effective coal movement and storage.

This study developed two models to determine optimal reorder points and order-up-to levels in situations with time-dependent and uncertain forecasted demand. Both models have advantages and disadvantages. The Sim-Opt model provides an interactive platform for tracking current inventory status and testing different order patterns using Excel functions. The company employs a periodic review policy to manage its inventory, which includes determining the reorder point (s) and order-up-to-level (S). The initial solution is constructed using the well-known concepts of Economic Order Quantity (EOQ) and Reorder Point. However, Excel Solver encounters difficulties in efficiently handling larger instances of the problem. A long-term lot sizing problem was addressed by implementing a Dynamic Programming model that considered warehouse capacity. The current models lack the capability to incorporate uncertainty in foretasted figures, but they can be rerun to generate forecasts for different scenarios.

The initial results indicate that the margin of error in total cost incurred for the Sim-Opt and Dynamic Model did not exceed 2%, indicating the suitability of the new model to simulate real data.

Scenario testing was conducted to consider uncertain data inputs. The analysis focused on examining the impact of simultaneous changes in demand season and price forecasting on inventory control activity. The results showed that price fluctuation greatly impacts the total cost, while limited capacity remains unchanged. The Dynamic Model performance also showed that only the total cost greatly fluctuates while the total number of orders remains unchanged.

Overall, The VBA code outperformed the Simulation in Excel in terms of execution speed and it can produce a long-term order plan, but the optimization heuristics in Excel Solver can output closer to optimal points.

6.2 Limitations of the Dissertation

One of the limitations of this research is the implementation of the capacitated lot size model in Excel Solver. While Excel Solver is a widely used optimization tool, it may have some constraints in handling complex and large-scale optimization problems. The capacitated lot size model involves multiple decision variables, constraints, and objective functions, which can potentially lead to challenges in terms of computation time and convergence. Excel Solver's efficiency in solving such complex optimization problems might be constrained by memory and processing limitations, resulting in longer solution times or even failure to converge in some cases. Furthermore, complex supply chain models often require advanced algorithmic approaches, sensitivity analysis, and scenario testing to account for various uncertainties and dynamic factors. Excel Solver's capabilities for handling stochastic programming, multiple scenarios, and advanced sensitivity analysis might be limited compared to more specialized software or programming environments.

Additionally, the scalability of Excel Solver might be a concern when dealing with larger datasets or longer planning horizons. The capacitated lot size model's performance could potentially degrade as the problem size increases, impacting the ability to analyze real-world scenarios accurately and efficiently.

One of the main challenges in demand forecasting is the inherent uncertainty and unpredictability of the coal quality. This makes it difficult to accurately predict future demand patterns, especially in volatile markets or during times of economic instability. The company is not able to control the origins of the coal. The developed model facilitated the company in recording the inventory status as well as the demand for consumables.

However, calculations were conducted to address a specific problem, assuming that the demand follows a normal distribution. In the future, this can be gathered as historical data and improve the demand distribution function.

6.3 Further Research

Future research should focus on inventory management in the presence of price uncertainty as price fluctuations have a substantial impact on a company's profitability. This could involve developing more sophisticated modelling techniques and integrating real-time data analytics and machine learning algorithms to improve the accuracy of price prediction.

Secondly, more complicated inventory models should be investigated as more data related to the company’s ordering practices and inventory is collected. Future research can focus on exploring other areas such as inventory models for multiple products that involve substitutions and random lead times.

Future research needs to re-evaluate the selected inventory settings for other types of demand distributions, such as Gamma or Poisson, under similar experimental conditions. The inventory control literature commonly employs the Normal or Gamma distribution to characterize demand during the lead time. The Poisson distribution is a suitable model for low-demand scenarios. This demand type exhibits significant variability and can also be intermittent, with periods of zero or low demand followed by demand peaks (Ramaekers & Janssens, 2009).

It is suggested that the simulation spreadsheet can be used for testing the optimization over additional scenarios. The industry supervisor suggested several scenarios of interest that have not yet been tested with the optimization due to time constraints. These include conducting tests over different lead times or incorporating a quantity discount for a guaranteed annual order quantity. Moreover, a MILP model can still be developed to solve the formulated CLSP, using more advanced computer software such as CPLEX, and Gurobi to reduce the computational time and achieve a global optimal point.

Additionally, further research could be conducted to determine if other companies in different industries have also benefited from this model. Furthermore, it would be interesting to investigate if the Heritage Railway Group specifically has implemented this model and observed positive outcomes in their demand forecasting process.

6.4 Personal Reflections

This summer project has provided the author with valuable insights into the complex domain of inventory models. With limited prior knowledge in this field, the author find that establishing this project was both challenging and exciting. The challenges faced during this project have enhanced my comprehension of inventory models and improved my ability to learn quickly.

The author's progress has been significantly influenced by their understanding and application of various inventory models and approaches. It is important to emphasize the significant contribution of the dissertation supervisor, who provided invaluable and constructive guidance in addressing the challenges encountered during various phases of the research process, notably in navigating issues related to methodology.

The author has derived significant personal and professional advantages from the research experience, particularly in terms of enhancing their time-management abilities. Each stage of the study had to be executed in a methodical and well-structured manner, taking into account temporal considerations. The author had to carefully plan and allocate time for each stage of the study to ensure its successful execution. Additionally, the challenges faced during this project have also highlighted the importance of adaptability and problem-solving skills in navigating complex domains like inventory models.

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Appendix I Description of demand data inputs

Field Description	Calculation methodology
Steam factor	Number of steam locomotive Refer to table 3
Diesel factor	Number of diesel locomotive Refer to Table 3
Coal demand for 5 round trip	=NORMINV(RAND(),2.55,0.225)
Warming fire factor	= 1 if the day before the steam locomotive was not used
Warming fire coal	=NORMINV(RAND(),0.3,0.045)
Steam raising fire coal	=NORMINV(RAND(),0.75,0.1125)
Daily Coal demand	= Steam factor * Coal demand for 5 round trip + Warming fire factor * Warming fire coal + Steam raising fire coal
Diesel for 4 round trip	=NORMINV(RAND(),12.2,0.915)*5*Diesel factor
Steam oil 220	=NORMINV(RAND(),1,0.025)*Steam factor
Bearing oil	=NORMINV(RAND(),6,0.15)*Steam factor

Appendix II Excel forecasting model for coal price (confident interval = 95%)

Date	Price in GBP	Lower Confidence Bound	Upper Confidence Bound
01/01/2023	260.26	260.26	260.26
01/02/2023	279.9247324	220.68	339.17
01/03/2023	293.1926519	213.44	372.94
01/04/2023	306.4605715	210.46	402.46
01/05/2023	319.728491	209.83	429.63
01/06/2023	332.9964106	210.74	455.25
01/07/2023	346.2643301	212.77	479.76
01/08/2023	359.5322497	215.65	503.42
01/09/2023	372.8001692	219.21	526.39
01/10/2023	386.0680888	223.33	548.81
01/11/2023	399.3360083	227.92	570.76
01/12/2023	412.6039278	232.90	592.30

Appendix III Pseudocode for the Simulation-Optimization problem with Warehouse capacity

Source: Developed from Liu et al. (2013) and Zhang et al. (2014)

Step 1: Initialization

#current objective function value

s = s' // Reorder point

Q = EOQ

S = S' = s + Q // Order-up-to level

A* = 1 // Direction of change for Q (increase)

A* = 1 // Direction of change for s (increase)

B = Q // Set of order quantities

Step 2: Simulation

Perform simulation over three-month period under (s', S')

Calculate the simulation objective value as I'

Add (s', S', I') into set P

Initialize variables for capacity constraint check:

max_inventory = 0 // Maximum inventory over all periods

for each period t from 1 to T:

Calculate I(t) - ending inventory for period t

Calculate I* - minimum positive inventory

Calculate I’ - absolute value of maximum negative ending inventory

max_inventory = max(max_inventory, I(t)) // Update max_inventory

Step 3: Increase or decrease reorder point

If /' < /, set s = s', S = S', / = /', and continue search as follows:

If A* = +1, set s' = s + I* and S' = s + Q to raise the smallest negative inventory to zero

If A* = -1, set s' = s - I* and S' = s + Q to lower the lowest positive inventory to zero

Go to Step 2

If I' > I, a local optimum under Q has been found, go to Step 4

Step 4: Increase or decrease Q

Let Q’ be the minimum of Q and Q* associated with (s, S)

If A* = +1, assign Q = Q’ + Q

If A* = -1, assign Q = Q’ - Q

If no Q exists inside (Q*, Q’), set A* = - A* (reverse search direction for order size Q)

If Q already exists in set B, go to Step 6

Otherwise, add Q to set B and go to Step 5

Step 5: Check capacity constraint for the current period and stock-out situation

if I(t) > 56:

// Handle capacity constraint violation (e.g., adjust order quantity)

Go to step 3

Step 6: Move to a new (s', S')

If $A^* = +1$, move to $(s' = s - Q, S = S)$ and set $A^* = 1$

If $A^* = -1$, move to $(s' = s, S' = s + Q)$ and set $A^* = -1$

Go to Step 2

Step 7: Termination

Output the best solution in set P

Appendix IV Descriptive Data Analysis of Demand Input

Data input for coal demand

Unit: Ton	Warming fire	Steam raising fire	5 round trips per day (11 miles per trip)
Mean	0.3	0.75	1.5
Fluctuation	+-30%	+-30%	+-30%
Min	0.21	0.525	1.05
Max	0.39	0.975	1.95
Range	0.18	0.45	0.9
Standard deviation	0.045	0.1125	0.225

Data input for diesel

Gallons	Class 33 (diesel)- 11 Miles/ 1.4MPG= 7.86 Gallons per round trip (red diesel) (to Norden)	Class 117 4 car DMU- 11 miles/ 0.9MPG= 12.2 gallons per round trip (red diesel) (to Norden)
Mean	7.86	12.2
Fluctuation	+-15%	+-15%
Min	6.681	10.37
Max	9.039	14.03
Range	2.358	3.66
Standard deviation	0.5895	0.915

Data input for oil

	Steam oil	220 Bearing oil
Mean	1	6
Fluctuation	+-5%	+-5%
Min	0.95	5.7
Max	1.05	6.3
Range	0.1	0.6
Standard deviation	0.025	0.15

Appendix V Sim-opt Models results for the year of 2022

Summary	Spring season (1)	Summer season (2)	Autumn season (3)	Winter season (4)
Initial Solution				
EOQ	11.38	17.93	16.37	11.27
Initial Reorder point (s)	21.16	52.48	47.12	26.76
Initial Order- up-to level (S)	32.54	70.41	65.00	38.03
Initial Total Cost	16963.01	88434.78	115840.23	46172.18
Total order (O)	3	10	9	6
Holding cost (H)	507.54	977.86	1272.78	763.84
Setup cost (S)	30	100	90	60
Optimal Solution				
Reorder point (s)	13.22	36.60	47.12	18.62
Order- up-to level (S)	26.44	50.31	65.00	28.73
Total Cost	16753.13	88089.95	115840.23	45991.85
Total order (O)	3	11	9	6
Holding cost (H)	297.66	623.03	1168.05	594.52
Setup cost (S)	30	110	90	60

Appendix VI Sim-opt Models: Difference scenarios testing for the year of 2023

Lower bound price forecast	Reorder point (s)	Order-up-to level (S)	Average unit price	Objective (TC)	Total order (O)	Holding cost (H)	Setup cost (S)	Product price (P)
Spring season (1)	11.52	16.93	231.82	18797.97	3	373.41	30.00	18394.56
Summer season (2)	20.83	35.13	231.82	58846.49	10.00	255.97	100.00	58490.51
Autumn season (3)	24.96	36.12	215.84	61185.39	10.00	333.75	100.00	60751.64
Winter season (4)	17.24	35.96	228.05	32605.14	6.00	382.87	60.00	32162.27
Total	/	/		171435.0	29	1346.01	290.00	169798.99

Upper bound price forecast	Reorder point (s)	Order-up-to level (S)	Average unit price	Objective (TC)	Total order (O)	Holding cost (H)	Setup cost (S)	Product price (P)
Spring season (1)	13.09	22.09	323.62	28596.11	3	525.32	30.00	28040.78
Summer season (2)	24.35	35.77	323.62	119274.35	10.00	634.55	100.00	118539.80
Autumn season (3)	21.98	31.18	502.94	140357.02	10.00	623.72	100.00	139633.30
Winter season (4)	16.49	23.31	570.62	79451.32	5.00	945.13	50.00	78456.20
Total	/	/		367678.79	28	2728.72	280.00	364670.08

Base price forecast	Reorder point (s)	Order-up-to level (S)	Average unit price	Objective (TC)	Total order (O)	Holding cost (H)	Setup cost (S)	Product price (P)
Spring season (1)	12.07	17.44	277.72	23318.68	3.0	433.33	30.00	22855.36
Summer season (2)	21.64	22.73	319.73	90194.59	10.0	414.65	100.00	89679.94
Autumn season (3)	22.08	32.50	359.39	102196.87	11.0	440.59	110.00	101646.28
Winter season (4)	17.92	30.64	399.34	56495.29	6.0	705.51	60.00	55729.78
Total	/	/		272205.44	30.0	1994.08	300.00	269911.36