mathematics

*Article*

# Cost of Ownership of Spare Parts under Uncertainty: Integrating Reliability and Costs

**Orlando Durán [1,*], Paulo Afonso [2], Víctor Jiménez [3] and Katty Carvajal [1]**

1 Escuela de Ingeniería Mecánica, Pontificia Universidad Católica de Valparaiso, Valparaiso 2340025, Chile; katty.carvajal.c@mail.pucv.cl
2 Centro Algoritmi, Departamento de Produção e Sistemas, Universidade do Minho, 4710-057 Braga, Portugal; psafonso@dps.uminho.pt
3 Departamento de Contabilidad y Finanzas, Universidad del Valle, Cali 760043, Colombia; victor.jimenez@correounivalle.edu.co
* Correspondence: orlando.duran@pucv.cl

**Abstract:** In capital-intensive organizations, decisions regarding capital costs play an important role due to the significant amount of investment required and the expected return on investment. Spare parts management is crucial to those ends, as spare parts management can constitute a significant portion of OPEX. Companies must implement a trade-off analysis between stock levels and assets' availability. Decision-making supports mechanisms such as the Level of Repair Analysis (LORA), Integrated Logistics Systems (ILS), and life-cycle costing (LCC) models have been developed to aid in equipment selection, implementation, and decommissioning. Nowadays, these mechanisms appear to be integrated with risk-management models and standards. This paper proposes a long-term costing model that integrates a capacity analysis, reliability functions, and risk considerations for the cost management of logistics activities, particularly in MRO structures. The model is built upon Time-Driven Activity-Based Costing (TD-ABC) and incorporates the volume of activities generated by MRO needs. It also addresses uncertainty through the integration of a cost-at-risk model. By integrating spare parts, activity-based cost models, and risk measurement through Monte Carlo simulation, this study offers powerful insights into optimizing spare parts logistics activities. The proposed model is a novel approach to include the risk of cost in spare parts management, and its matrix-activity-based structure makes possible the development of sophisticated mathematical models for costing and optimization purposes in different domains.

**Keywords:** costing systems; TD-ABC; spare parts; reliability; uncertainty; risk

**MSC:** 91B32

check for updates

**Citation:** Durán, O.; Afonso, P.; Jiménez, V.; Carvajal, K. Cost of Ownership of Spare Parts under Uncertainty: Integrating Reliability and Costs. *Mathematics* **2023**, *11*, 3316. https://doi.org/10.3390/math11153316

Academic Editors: Huajun Tang, Jun Wu, Huimin Jiang and Ivan Lai

Received: 19 June 2023
Revised: 21 July 2023
Accepted: 25 July 2023
Published: 28 July 2023



## 1. Introduction

In capital-intensive organizations, decisions regarding capital costs play an important role due to the significant amount of investment required and the expected return on investment. The availability and operational efficiency of these capital assets throughout their life cycles are essential. To achieve maximum availability, organizations implement complex maintenance and support activities, including maintenance, repair, and overhaul (MRO) structures, as well as preventive procedures and logistics for components. These activities incur both in capital costs (CAPEX) and operational costs (OPEX), necessitating the use of cost breakdown structures (CBSs).

In capital-intensive organizations, the costs of ownership occupy a relevant position in decision-making processes [1]. This is mainly due to the high cost that these assets have and the expected return on investment that they must generate or are expected to generate. Furthermore, it is expected that these capital assets will be available and maintain operational efficiency throughout their extended life cycles. This means that organizations must deploy intense efforts so that the availability of these assets is as close to 100% as possible. That is why these organizations establish a complex set of maintenance and support activities in order to guarantee operational continuity, namely maintenance, repair, and overhaul (MRO) structures [2]. Moreover, careful prevention procedures are established. In addition, forecasting procedures and logistics of components mechanisms that lead to important investments, expenses, and costs have to be implemented in such organizations. These costs are usually subdivided into capital costs (CAPEX) and operational costs (OPEX). As a consequence, the need arises for cost breakdown structures (CBSs) that incorporate a complete and complex list of cost elements [1]. Within the cost elements of the aforementioned structure, and specifically within the OPEX, spare parts (SPs) costs are indicated [3].

At the beginning, organizations would simply react to failures in their maintenance approach. They waited for issues to arise before acting and making repairs. The support structures were minimal, and the processes showed great instability. Over time, strategies have changed to incorporate preventive actions and efforts to predict the moment and magnitude of failure. In recent years, these strategies have been incorporating learning capabilities based on machine-learning techniques, aiming to establish and develop intelligent maintenance systems with prescriptive capabilities within the context of cyber–physical systems [3–5]. This brought with it an increase, both in number and complexity, of support and maintenance structures for these organizations, bringing, in certain cases, the settlement of heavy and costly approaches and strategies. This situation brought with it the need to look at the physical assets management (PAM) from a long-term perspective and focused on the concept of value adding. That is why the creation, development, and application of decision-making support mechanisms that facilitate the selection, construction, implementation, maintenance, and decommissioning of equipment are necessary. Among these mechanisms, there is the Level of Repair Analysis (LORA), the Integrated Logistics Systems (ILS), and the life-cycle costing models [6]. More recently, those mechanisms have been integrated into risk management models (ISO 31000) [7] and ISO 55000 [8].

It is known that, within the cost breakdown structures of the plant life-cycle cost, it is observed that operational and maintenance support costs make up over 60% of the total, with spare parts' costs representing approximately 25% to 30% of such costs [9]. This is why organizations approach this issue as a trade-off analysis between components' stock levels and the company's capabilities to achieve high levels of availability. Another important situation to consider is the high number of items that companies must manage to support maintenance activities. These elements (stock-keeping units, SKUs) can reach tens or hundreds of thousands of items inside the warehouses. This leads to the existence of heavy organizational structures to provide adequate management of the aforementioned items. Nonetheless, it is essential to manage these elements with a meticulous sense of prioritization or hierarchy [10,11].

For this reason, holding-cost-management models have lately come to be seen as value aggregation analysis models [12]. Despite the fact that the ISO 55000 [13] standard declares relevant the management of costs related to the components' logistics, the level of detail that these models have does not allow for the correct management of activities related to MRO structures in the long term. However, increasingly, some companies have sophisticated data structures and information processing (Industry 4.0, big data, etc.) for these ends.

This paper proposes a long-term costing model for management logistics activities which integrates a capacity analysis and reliability functions as a means of incorporating the risk associated with the management of physical assets (e.g., spare parts), as is fundamental in modern logistics. The proposed model is based on the Time-Driven Activity-Based Costing (TD-ABC [14]) and captures the volume of activities that are executed according to the needs generated by the MRO activities.

Furthermore, this article includes the uncertainty of carrying out maintenance activities that create variability in the estimation of total costs. In addition, this paper presents a cost at risk model (CaR [15]) and also includes the time value of money to calculate the present value of such costs.

In this article, three fields of knowledge are integrated: spare parts, activity-based cost models, and risk measurement through the Monte Carlo simulation. This work is organized as follows: in the next section, a brief review of the related literature is made. In Section 3, the model is presented; in Section 4, an application case is provided; and in Section 5, the results are discussed, along with future developments. Finally, the conclusions are discussed.

## 2. Theoretical Background

The two approaches aimed at the long-term economic evaluation of the holding and management costs of physical assets recurrently cited in the literature are life-cycle costing (LCC) [16] and total cost of ownership (TCO) [17]. Life-cycle cost (LCC) is a comprehensive method for assessing the total cost of an asset, as it includes all of the costs associated with the asset over its lifespan. TCO can be viewed as a simpler method that can be used to compare the costs of different suppliers of assets, materials, products, or services.

According to Maisenbacher et al. [18], these methodologies have proven to be highly reliable, enabling an accurate and comprehensive evaluation of all capital and operation costs of different types of investments in production systems. As a result, a range of models have been proposed to estimate life-cycle costs in complex industrial facilities. Some models, such as the work of Woodhouse [19], are characterized by the assumption of a constant failure rate over the useful life of the asset. Other models have been proposed for specific installations or systems, however, in general terms.

Even so, there are several standards that define the guidelines for estimating life-cycle costs, including the IEC60300-3-3 standard [20]. Additional standards for specific types of installations are as follows: ISO 15663-2 [21] for oil and gas; SEMI E35-0618 (2018) [22] for the semiconductor industry; ASTM E917-17 (2017) [23], ISO 15686-5 (2017) [24], and APPA 1000-1 (2018) [25] in the construction sector; and NATO-ALCCP-1 (2018) [26] for the military sector.

Every estimation model of the LCC or TCO type assumes different assumptions regarding the costs and behavior of the system or organization at different moments in time. Consequently, it is necessary to create and apply costing techniques that simplify the costing and allocation processes without significantly affecting the accuracy of the results. Among these techniques, we can highlight those based on Activity-Based Costing (ABC) [27].

Despite being recognized as a useful tool for calculating life-cycle costs (for example, [28,29]) ABC presents, as a main disadvantage, difficulties in its implementation. The excessive number of activities and drivers makes it difficult to obtain satisfactory results in its implementation and use. Thus, the Time-Based ABC (TD-ABC [14]) is a good alternative to estimate the costs of processes and cost objects. In this new approach, a single driver is used: the time required for the execution of each activity. Through the use of this driver, the specific characteristics among the different cost objects are captured more accurately.

Although the economic impact of ownership and managing costs of critical spare parts is still significant and increasing [30], no Total Cost of Ownership (TCO) model currently incorporates or appropriately evaluates the influence of spare parts logistics costs on the overall ownership costs.

Another important variable for decision-making has to do with variability, whether internal or external to production processes. Variability is related to uncertainty and risk in decision-making [31]. Uncertainty in a phenomenon can arise from various conditions, including limited and complex information; human errors; and external factors such economic, political, and social changes [32–34]; Nachtmann and Needy [35] state that uncertainty is linked to the potential for errors resulting from incomplete information about a phenomenon and its environment. Therefore, there exists a direct relationship between information complexity and the level of uncertainty in a phenomenon.

The term "risk" is used in a variety of settings and can convey different meanings. Generally, risk refers to the effect of uncertainty on objectives—where an effect is a deviation from the expected outcome (positive and/or negative) [36].

By quantifying the variability of costs, it is possible to address questions such as the following: What is the level of cost risk associated with contracts and projects? Which variables, products, processes, or services contribute most to cost variability and should therefore be subject to tighter control? How can we define measures and implement risk mitigation actions, as well as evaluate the impact of such interventions? Traditionally, both researchers and practitioners have primarily relied on deterministic costing models, neglecting to properly acknowledge and manage cost uncertainty.

Several techniques are employed to capture uncertainty, including decision trees, Markov modeling, fuzzy logic, discrete event simulation (DES), and Monte Carlo simulation (MCS) [37–41]. The choice of an appropriate method for modeling uncertainty depends on the specific problem being addressed.

Notably, the two prominent methods to address the challenge of uncertainty in mathematical models are the Monte Carlo simulation and fuzzy methods [42]. In the context of costing systems, several authors have explored the topic of uncertainty using either the Monte Carlo Simulation or fuzzy methods [28,43–47].

The Monte Carlo simulation, as an approach for managing uncertainty and quantifying risk, has been used in several fields of knowledge, including risk quantification in costing systems [48]. Among the advantages of the Monte Carlo simulation are the ability to include probability distributions of variables, the ability to include correlations of variables, and the ability to obtain solutions in reasonable computational times.

Fuzzy logic, introduced in the 1960s, aims to quantify imprecision and uncertainty [49]. In fuzzy sets, the primary objective is to measure inaccurate information [50]. In terms of variability, costs, and measurement of various risks, Reference [35] studied different methodologies to quantify uncertainty in Activity-Based Costing models. Other authors have related variability, uncertainty, and risk in cost systems through fuzzy logic [39,51,52]. The field of fuzzy theory includes the analysis of theory, sets and fuzzy numbers. Fuzzy sets allow for uncertainty based on the judgment of experts [53].

Some other commonly used methods include interval mathematics, probability theories, approximate set theory, and theory of evidence, which propose mathematical models to handle and measure uncertainty. Interval mathematics offers a straightforward representation of uncertainty by defining lower and upper limits but it does not consider probabilities into the model [29,49].

A generic risk management process includes the following steps: (1) context establishment, (2) risks identification, (3) risk assessment (the process of measuring the level of risk, expressed in terms of the combination of consequences and likelihood), (4) risk evaluation, and (5) risk treatment/control [36].

In this paper, we propose a matrix-based Activity-Based Costing (ABC) model for LCC estimation and include inherent variability in processes through Monte Carlo simulation, allowing us to obtain financial metrics for short-, medium-, and long-term decision-making. Monte Carlo simulation is a quantitative technique that utilizes statistics and computers to simulate, through mathematical models, the random behavior of real systems [54].

The key to the Monte Carlo simulation is to create a mathematical model of the system, process, or activity under analysis, identifying those variables—model inputs—whose random behavior determines the overall system's behavior. Then, random samples are generated for these inputs, and the system's behavior is analyzed based on these generated values. After repeating the event n times, n observations about the system's behavior are available [55].

The Monte Carlo simulation has been applied in numerous fields as an alternative to exact mathematical models or even as the only means of estimating solutions for complex problems. Therefore, nowadays, it is possible to find models that use the Monte Carlo simulation in areas such as information technology, the energy sector, business, economics, industry, and even social contexts [55–59]. The Monte Carlo simulation can be used in all fields where behavior is random or probabilistic.

## 3. Materials and Methods

In the previous section, we described the main theoretical foundations of this research, and in this section, we describe the methodological aspects on which our proposal is based.

In this research project, a Design Science Research (DSR) approach was followed [60]. In DSR, the goals of research are very pragmatic; therefore, it can be used in specific projects with characteristics and, although generalization is not one of the strengths of this method, the results can be extrapolated to projects with similar characteristics. The approach of DSR generally requires the creation of an artifact, theory, model, or design as a means of presenting, understanding, and/or improving a reality [54,61,62]. This paper proposes a TD-ABC model to tackle the complexity of spare parts logistics and captures the volume of activities that are executed according to the needs generated by the MRO activities and spare parts management in a long-term approach. In addition, the proposed model admits the uncertainty using a cost-at-risk (CaR) model considering the time value of money to calculate the present value of such costs.

The model presented below is based on the following fundamental elements.

There is a set of activities related to logistics and spare parts management processes. These activities are carried out to meet the consumption needs of customers and are made up of stages in a logistics chain that begins with the arrival of items at the warehouse and concludes with the activities of providing components to customers (e.g., maintainers). These relationships are represented based on a TD-ABC matrix model [63].

On the other hand, Weibull reliability functions [64] are included for each type of component that allow for the estimation of component failure rates and, therefore, the number of activities that are or will be performed by the spare parts logistics system. One of the most notable aspects of this research is the use of matrices for the representation of the costs. The most important elements of this methodology are described in the next section. Figure 1 shows the global process of the spare parts ownership costing model. The use of reliability information in the TDABC system improves the method of estimating parameters of consumption of the spare parts throughout time. Using this model enables us to consider the inherent variability of the quantity of consumed spare parts and to examine the effects of inherent uncertainties in a risk analysis.

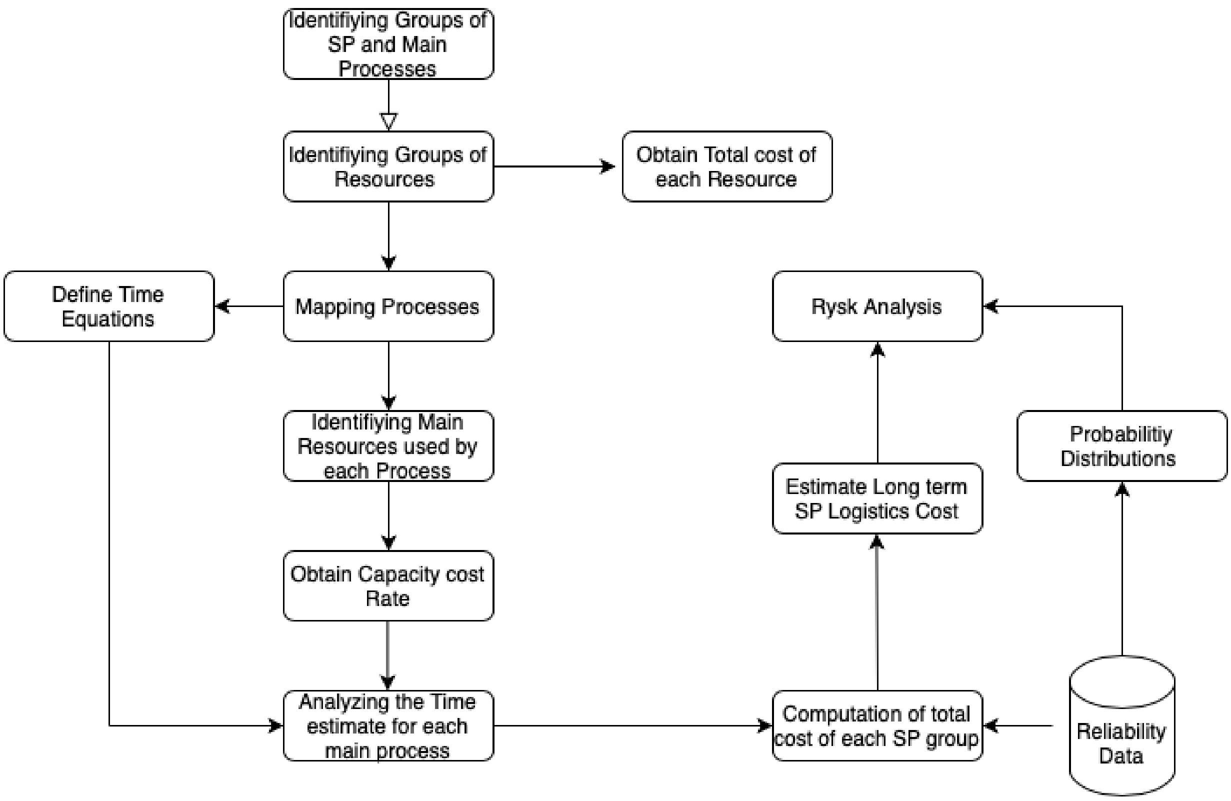



**Figure 1.** A combined conceptual model based on Time-Driven ABC, reliability, and risk analysis.

### 3.1. Matrix Model for TD-ABC

Suppose the organization identifies a set of $j$ resources, which have a cost, $C_j$, for a given period. A set of $m$ activities performed by the organization is also considered. On the other hand, there is a set of $k$ components (spare parts) that are managed by the organization.

The calculation of the capacity cost rate (\$/time unit) corresponds to the quotient between the costs of resources used in a given period ($C_j$) and the practical capacity available $(P'_j)$ for the period under analysis.

$$V_j = \frac{C_j}{P'_j} \tag{1}$$

The product between the unit time that each activity $m$ consumes each resource $j$ ($UT_{mj}$) and the capacity cost rate ($V_j$) allows us to obtain a vector with the values of the resources effectively used by the activities during the given period $(R')$.

$$R' = UT_{mj}\, V_j \tag{2}$$

$Q_{km}$ corresponds to quotient between the number of times that the activity $m$ is executed to serve the component $k$, divided by the total times activity $m$ is executed. These quantities depend on the necessary or forecasted logistical transactions during the life cycle for each spare part ($k$). Those numbers of transactions can be estimated through a reliability model, as is explained later in this paper.

Finally, the total effective cost of the logistical and SP management processes for each component $k$ ($CT_k$) is given by the following product:

$$CT_k = Q_{km} UT_{md}\, \frac{C_j}{P'_j} \tag{3}$$

### 3.2. Concept of Life Cycle in Time Equations

The concept of life cycle, from a multiperiod approach, was incorporated into the time equations of the TD-ABC model. Using time equations, the time consumed by an activity can be expressed as a function of different characteristics of the components. These are called time drivers. The general equation of time used in the overall formulation of the TD-ABC is as follows:

$$t_m = \beta_0 + \beta_1 * x_1 + \ldots + \beta_p * X_p \tag{4}$$

where we have the following:

$t_m$ = Time required to execute the activity $m$ considering different components or particularities of them.
$\beta_o$ = Base time consumed by activity $m$, regardless of the characteristics of cost object $k$.
$\beta_i$ = Unit time additionally consumed by due to specific characteristics of the cost object $k$.
$p$ = Number of time drivers or differentiating characteristics for activity $m$.
$x_1$ = The quantity consumed of a given SP (or family of SPs).

The cost of each activity is calculated as the product of the time required by the activity and the cost per unit of time. From the life-cycle cost point of view, the composition of the time equations should reflect the variation over the periods ($y$) of the considered life cycle ($y$ = 1,. . ., $cv$). This occurs as a function of the behavior dynamics of the drivers throughout the lifecycle of a physical asset or a set of assets. This can be represented by the quantities of components that have different characteristics (different time drivers), as follows.

$$t_{ljy} = \beta_{0y} + \beta_{1y} * \frac{\lambda_{ky1}}{q_{ky1}} * x_{1y} + \beta_{2y} * \frac{\lambda_{ky2}}{q_{ky2}} * x_{2y} + \ldots + \beta_{py} * \frac{\lambda_{kyp}}{q_{kyp}} * x_{py} \tag{5}$$

where $x_{iy}$ represents the quantity consumed of a given SP (or family of SPs) in a period $y$, and which corresponds to a given characteristic $p$. On the other hand, $q_{kyp}$ corresponds to the lot size of the spare part $k$, in year $y$, considering driver (characteristics) $p$. Moreover, $\lambda_{kyp}$, represents the failure rate of the spare part $k$, considering its $p$ characteristic, during the period $y$.

### 3.3. Reliability Model

The most direct and accurate way to obtain failure rates throughout the life of a component is by using models based on component reliability. In this section, it is explained how these rates were obtained using Weibull functions.

All equipment must be maintained when used because, during use, it undergoes deterioration processes that lead to loss of efficiency and/or failures. These failures will affect the availability of the equipment. Along with this, many (non-repairable) components will have to be replaced. Usually all equipment, throughout its life cycle, presents different behaviors in terms of its failure rate. As an example of this, there is a model widely cited in the literature, the so-called "bathtub curve model" [65]. This model establishes a life cycle composed of three phases: beginning of life (BOL), middle of life (MOL), and end of life (EOL). During these phases, the equipment presents different levels of reliability and failure rates. In the first phase, the equipment generally behaves according to the so-called infant mortality. Here, the failure rate decreases as time progresses. In the second phase, called useful life, the failure rate behaves in a constant manner. Finally, in the final phase, usually called the wear phase, the failure rate ($\lambda$) has a noticeable ascending behavior.

The Weibull function is one of the statistical distributions commonly used to represent the reliability behavior over the useful life of a piece of equipment. Therefore, the reliability of a component can be represented by the following equation:

$$R(t) = e^{-(t-t_0/\eta)^{\beta}} \tag{6}$$

where we have the following:

$\beta$ = Shape factor that characterizes the failure pattern.
$\eta$ = Scale parameter, which represents the characteristic life of the equipment. The characteristic life is given by the time when the failure probability is 63.2%.
$t_0$ = Location parameter that represents the beginning of the deterioration process. It is also considered as the first moment in which a failure can occur (estimate).

Therefore, by knowing or estimating the Weibull parameters, it will be possible to estimate the failure rate and, therefore, the requirements or needs for components to replace in the future. This relationship is given by the following equation:

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{7}$$

The failure rate of a component and, consequently, the demand rate for a new non-repairable part in the warehouse can be represented by specific combinations of Weibull parameters. By changing the values of the Weibull parameters over the lifetime of a given piece of equipment, it is possible to model the behavior of different drivers in the costing system.

### 3.4. Integration of Both Models and Computation of Risk Measures

As mentioned above, the matrix $Q_{km}$ represents the consumption of activities $m$ per component $k$ in the spare parts warehouse. Therefore, the number of executions of activities in a certain period, also called transactions, is considered to be proportional to the number of units of spare part $k$ needed in the same period $y$. In turn, and as already mentioned, the units of component $k$ that are required in the warehouse will correspond to the units that suffer failures during a certain period $y$, plus a fraction of units attributable to preventive replacements in the same period. The total of those units is represented by $\lambda_{ky}$.

It is worth noting that certain activities are carried out while considering a certain batch size. This means, for example, that when a component enters the warehouse and it is purchased in batches of specific sizes (EOQ, for example), the execution time must be subdivided into the number of units that make up that batch. This batch size will be called $Q_{km}$. According to the previous section, the matrix $Q_{km}$ must be redefined to incorporate the batch size of components $k$ in relation to which each activity $m$ is performed:

$$Q_{km} = \begin{bmatrix} \frac{\lambda_{11}}{q_{11}} & . & . & \frac{\lambda_{1m}}{q_{1m}} \\ \frac{\lambda_{21}}{q_{21}} & . & . & \frac{\lambda_{2m}}{q_{2m}} \\ . & . & . & . \\ \frac{\lambda_{k1}}{q_{k1}} & . & . & \frac{\lambda_{km}}{q_{km}} \end{bmatrix} \tag{8}$$

In summary, Equation (3) can be redefined as follows:

$$\begin{bmatrix} CT_{1y} \\ . \\ . \\ . \\ CT_{ny} \end{bmatrix} = \begin{bmatrix} \frac{\lambda_{11}}{q_{11}} & . & . & \frac{\lambda_{1m}}{q_{1m}} \\ \frac{\lambda_{21}}{q_{21}} & . & . & \frac{\lambda_{2m}}{q_{2m}} \\ . & . & . & . \\ \frac{\lambda_{k1}}{q_{k1}} & . & . & \frac{\lambda_{km}}{q_{km}} \end{bmatrix} \begin{bmatrix} UT_{11} & UT_{12} & . & . & UT_{1d} \\ UT_{21} & UT_{22} & . & . & UT_{2d} \\ . & . & . & . & . \\ . & . & . & . & . \\ UT_{m1} & UT_{m2} & . & . & UT_{md} \end{bmatrix} \begin{bmatrix} \frac{C_1}{P_1'} \\ \frac{C_2}{P_2'} \\ . \\ . \\ \frac{C_d}{P_j'} \end{bmatrix} \tag{9}$$

Once the deterministic model has been built, it is possible to identify which parameters of the model show variation, and using statistical tests of goodness or focus groups with specialists, it is possible to estimate the empirical probability distributions of the parameters that show variability. Thousands of possible scenarios are created considering the probability distribution function of the input parameters, which, in this case, are related to failure rates and resource consumption by activities. These scenarios allow us to obtain the probability function of the total cost. An important aspect is that this model considers the possible correlations that may exist between the different parameters of the model.

With the probability distribution of the cost, measures such as the cost at risk (CaR) can be calculated, which would be the maximum expected cost with a certain level of confidence for each of the analysis periods; and the present cost value at risk (PVCaR), which would be the present value of cost at risk, which includes the risk measurement and the time value of money.

## 4. Case Study

The proposed model, based on a matrix representation for TD-ABC, and incorporating reliability functions as a means of sizing the elements of the timing equations, was applied in a real industrial context.

The case study is a distribution center (DC) for components of a well-known Japanese manufacturer of heavy equipment for construction and mining. This DC is located in Northern Chile and has 2000 $m^2$ of a covered area, plus 2350 $m^2$ of outdoor area where large components are stored. The organizational structure is made up of four main areas, namely reception of domestic components and fungibles, reception of imported components, consolidation and dispatch, and inventory management area. This center is responsible for the distribution of SPs that are requested by a series of consumption units, which are mainly mining operations. There are about 11,000 components on the DC that are divided into three main categories: large (A), medium (B), and small (C). For these, there are three types of storage positions available, which are defined below:

Storage zones: Intended for large components. Most type A spare parts are in those zones.

Storage racks: Which can be found both, in the covered part of the property and in the outdoor. These shelves contain most of the type B spare parts.

Storage boxes: They are small shelves. These boxes are used to store mainly *C*-type parts.

The DC operates with three categories of consumption units:

- Contracts with mining companies: The DC's owner maintains contracts with several mining companies. In this case, SP units are prepared and shipped from the DC to the specific mining location.
- Sales: The DC also provides component sales to customers who own the equipment manufactured by the company.
- Imports: The company has several branches throughout the world, including in Mexico, Australia, and Peru, among others. If the center does not have the necessary parts, it requests the nearest branch to have the item available, so as not to jeopardize customer-service levels.

The components undergo the following processes as they pass through the warehouse.

A. Reception: Once the transport arrives at the warehouse, the reception process is carried out as follows:
    - Verify purchase order: This is the process in which the person in charge verifies the quantity of units which are received.
    - Registration in the ERP system: Input into the information system for the inventory to be updated.
    - Quality Control: It is verified that the items are in optimal condition, to be used without any type of inconvenience.
    - Quantity checking: Verifying that the quantities described are exactly those declared by the purchase order. Checking the quantity of components in some cases is very stressful because there are occasions when the components are very small and come in large quantities, such as washers, nuts, small screws, etc.
B. Storage: Once unpacked, the components are transported to storage areas. The type of transport used to bring components to their location depends on their dimensions. The types of transport are as follows:
    - Collection service order: For most cases, it is used for C-type spare parts.
    - Transfer by 3-ton crane: Used for components categorized as type B.
    - Crane transfer of up to 10 tons: Used for type-B and type-A components.
C. Picking and shipment of spare parts. This process is carried out through the following phases:
    - Picking: This activity consists of gathering all the SPs of the purchase order in a specific place for verification and preparation, together with the document called the "pick service order". Usually, this activity is also called kitting.
    - Item-by-item verification: The "pick service order" is verified by a person in charge; if the necessary stock does not exist, the warehouse manager is informed.
    - Inventory reduction: Consequently, after confirming the entire purchase order, the inventory is discounted by updating the warehouse stock in the information system.
    - Packaging: Performed to protect each SP before shipping.
    - Consolidation: Consists of leaving the package ready for transport at the place indicated by the company in order for it to be collected by the transport firm. At the end of consolidation, it is registered that the order is ready to be withdrawn.

For this case study, we considered a set of orders in the warehouse, covering the last 7 years. In order to streamline the analysis, a decision was made to select a representative component from each category (A, B, and C) that accurately reflects the behavior of the components within that category.

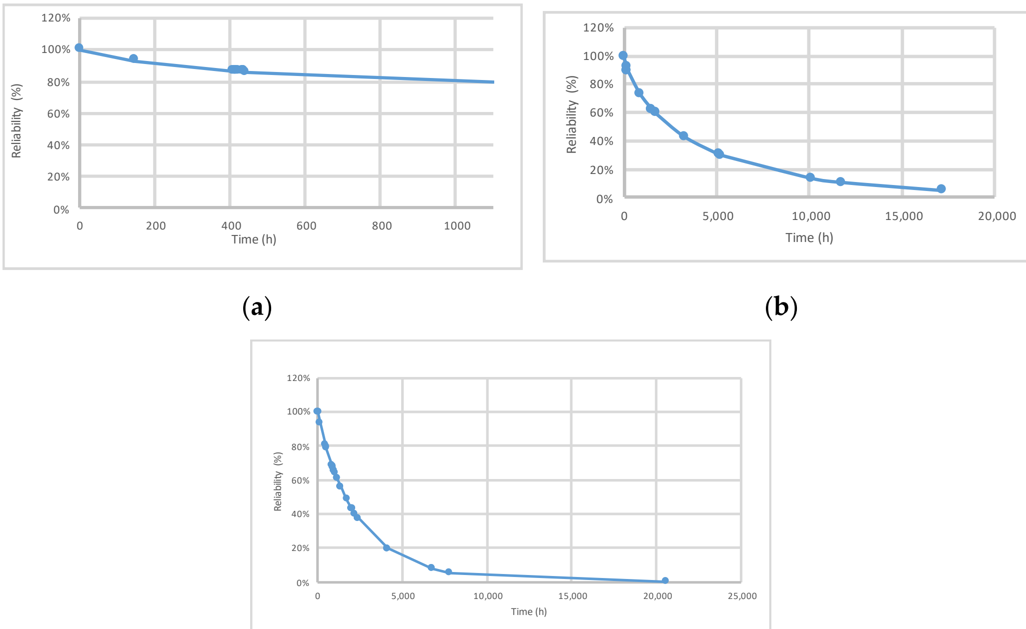
For each of the three selected components, it was assumed that the time between orders would be considered the mean time between failures (MTBFs) of the reference component of each category, in such a way that each component reorder request corresponds to a failure of a component in the field (corrective replacements only). From the failure history, the reliability parameters, using the Weibull distribution, were calculated. Subsequently, using such parameters, consumption projections were made for each period of the components' life cycle (*cv*), considering, separately, each of the three categories of SPs under study.

Table 1 presents the values of the Weibull parameters together with the parameters of the adjustment tests by the Kolmogorov–Smirnov method.

**Table 1.** Reliability parameters using Weibull's distribution for each spare part category.

| SP Categories | Failures/Year | $\beta$ | $\eta$ | $\gamma$ | $\lambda$ | MTBF (h) |
|---|---|---|---|---|---|---|
| Small SPs | 36 | 0.6568 | 7.812 | 0 | 3 | 10.552 |
| Medium SPs | 15 | 0.755 | 4.102 | 0 | 4 | 4.858 |
| Big SPs | 31 | 0.9204 | 2.438 | 0 | 4 | 2.535 |

Figure 2a–c shows the reliability curves for each of the three categories of components. Those figures illustrate reliability over time and demonstrate how reliably the components operate or remain functional throughout the utilization time. The lines indicate the percentage of time they remain functional or available for utilization. By analyzing the reliability graphs, one can gain insights into the overall performance and availability of each component and assess or estimate the future replaceable components needed.




(**a**) (**b**)

(**c**)

**Figure 2.** Behavior of reliability over time for the three categories of spare parts: (**a**) small, (**b**) medium, and (**c**) large.

By using the obtained Weibull parameters and Equation (7) ($\lambda$), it was possible to estimate the corresponding failure rates and future consumption of each of the three categories of spare parts. Bear in mind that each category of component is made up of a different number of components. Therefore, the number of consumptions for each period, according to each category, corresponds to the product between the corresponding failure rate and the quantity of components in each category (A, B, or C). Next, we present the details of the application of the proposed model in the previously described case.

## 5. Time-Driven Activity-Based Costing Model with Component Reliability

For the application of the Time-Driven Activity-Based Costing model, in the first place, the processes and activities needed for managing the spare parts warehouse must be established. Table 2 shows the list of activities which were described in Section 2. In the second place, the resources needed to perform the activities must be defined. In the third place, the times allocated to each of the activities must be estimated, considering each type of SP category. That estimation was carried out by a set of the DC's supervisors and a group of direct workers in a succession of several meetings.

**Table 2.** Activities and sub-activities.

| Activities | | Sub-Activities | |
|---|---|---|---|
| 1 | Reception | 1.1 | Check purchase order |
| | | 1.2 | Quality review |
| | | 1.3 | Quantity review |
| | | 1.4 | Determine if the location matches the size |
| 2 | Storage parts | 2.1 | Print and pick up stamps |
| | | 2.2 | Transfer to the storage place |
| | | 2.3 | Confirm if the SP is in the warehouse |
| 3 | Collection and dispatch of spare parts | 3.1 | Collection of items for dispatch |
| | | 3.2 | Reduce inventory |
| | | 3.3 | Pack order |
| | | 3.4 | Deliver picking to issue dispatch guide |

The warehouse was constructed in a rented location. For its appropriate operation, 16 workers are needed. Two sizes of forklift trucks are used to move the materials, that is, according to the different dimensions and weights of the SP. The summary of the resources needed to perform the activities on the DC is presented in Table 3. The information was obtained from the organization's enterprise resource planning system.

**Table 3.** Amounts of resources consumed (per month).

| Resources | | Amount |
|---|---|---|
| 1 | Rent | $15,000,000 |
| 2 | Salaries | $19,500,000 |
| 3 | Electricity | $1,513,300 |
| 4 | Water | $1,620,360 |
| 5 | Telephone | $500,000 |
| 6 | Food | $5,546,590 |
| 7 | Security services | $5,581,535 |
| 8 | Cleaning services | $4,028,288 |
| 9 | Waste removal | $355,000 |
| 10 | Minor maintenance | $1,080,000 |
| 11 | Corrective system maintenance | $1,150,000 |
| 12 | Green areas maintenance | $402,048 |
| 13 | Pest control | $150,000 |
| 14 | Purified water supply | $90,250 |
| 15 | Air-conditioning maintenance | $1,204,800 |
| 16 | Personnel transportation | $2,698,427 |
| 17 | Supplies | $300,000 |
| 18 | Machinery, 3 tons | $4,753,760 |
| | Machinery, 10 ton | $5,038,986 |
| | Total (month) | $70,513,344 |

According to the objectives of obtaining the number of spare parts units requested and moved in the warehouse, and thus projecting the utilization of existing capacities (resources), an estimation was made from year 1 considering 12 months (resources costs equal to those in Table 3). For this reason, based on the value during the first year, resource values were projected for the next five years, considering estimated inflation values (Table 4).

**Table 4.** Estimation of resources consumed per year.

| Year | Inflation | Resources |
|---|---|---|
| 1 | 2.30% | $846,160,123 |
| 2 | 2.60% | $868,160,286 |
| 3 | 2.90% | $893,336,935 |
| 4 | 3.20% | $921,923,717 |
| 5 | 3.50% | $954,191,047 |
| 6 | 3.80% | $990,450,306 |

The warehouse's working hours correspond to 8 h a day, and it works 22 days a month, for 12 months a year. This warehouse has 16 workers who carry out the activities, corresponding to approximately 33,792 man hours (HH). This capacity corresponds to the theoretical capacity; to obtain the available practical capacity, we consider an efficient factor equal to 80%. Thus, the available practical capacity will be 27,033, 6 h per year. The practical capacity rate corresponds to the value in ($/time unit) obtained through the ratio between the value of projected resources per year (Table 5) and the effective or practical capacity available.

**Table 5.** Activities' execution times for SPs in the warehouse (in min/batch).

| | Activities | Big Spare Parts | Mid. Spare Parts | Small Spare Parts |
|---|---|---|---|---|
| 1. | Check purchase order | 10 | 15 | 30 |
| 2. | Quality inspection | 20 | 10 | 5 |
| 3. | Quantity verification | 15 | 15 | 25 |
| 4. | Verify if location corresponds to size | 10 | 10 | 10 |
| 5. | Print and affix corresponding labels | 5 | 5 | 5 |
| 6. | Transfer to storage location | 10 | 10 | 10 |
| 7. | Confirm item by item in system if the SP is in stock | 10 | 10 | 10 |
| 8. | Collect spare parts for dispatch | 15 | 10 | 5 |
| 9. | Deduct from inventory | 5 | 5 | 5 |
| 10. | Pack order | 20 | 10 | 5 |
| 11. | Provide picking for subsequent dispatch guide | 10 | 10 | 10 |

As already mentioned, the execution times of the activities were obtained directly from the company through interviews with the supervisors and workers responsible for each of the processes and activities. These times are shown in Table 5.

### 5.1. Time Equations

The time equations correspond to each activity performed in the warehouse. Therefore, we have here 11 time equations, corresponding to each of the 11 activities, as shown in Table 5. Each time equation ($T_i$) considers that the time consumed by the sub-activity depends on the SP category. In this case, and as mentioned earlier, the SP categories are large (L), medium (M), and small (S). Therefore, $X_{np}$ corresponds to the number of lots (set of SPs of the same type and category that pass through each activity). The values of $X_{np}$ correspond to the component failure rate, $\lambda_{km}$, divided by the number of units per batch, $Q_{km}$. The projected values of failure rates for each spare part category in each year ($\lambda_{km}$)

are obtained from Equation (7), using the Weibull parameters for each category (Table 1). Therefore, and considering the values in Table 5, the equations are as follows:

$$T_1 = 10 * X_{11} + 15 * X_{12} + 30 * X_{13} \tag{10}$$

$$T_2 = 20 * X_{21} + 10 * X_{22} + 5 * X_{23} \tag{11}$$

$$T_3 = 15 * X_{31} + 15 * X_{32} + 25 * X_{33} \tag{12}$$

$$T_4 = 10 * X_{41} + 10 * X_{42} + 10 * X_{43} \tag{13}$$

$$T_5 = 5 * X_{51} + 5 * X_{52} + 5 * X_{53} \tag{14}$$

$$T_6 = 10 * X_{61} + 10 * X_{62} + 10 * X_{63} \tag{15}$$

$$T_7 = 10 * X_{71} + 10 * X_{72} + 10 * X_{73} \tag{16}$$

$$T_8 = 15 * X_{81} + 10 * X_{82} + 5 * X_{83} \tag{17}$$

$$T_9 = 5 * X_{91} + 5 * X_{92} + 5 * X_{93} \tag{18}$$

$$T_{10} = 20 * X_{101} + 10 * X_{102} + 5 * X_{103} \tag{19}$$

$$T_{11} = 10 * X_{111} + 10 * X_{112} + 10 * X_{113} \tag{20}$$

To test two possible scenarios, we consider two possible situations in the behavior of failure rates for each category of components:

1. Considering constant rate values for the next 6 years;
2. Considering that rates in the future will tend to increase, that is, a Weibull $\beta$ value > 1, which corresponds to the wear phase of the bathtub curve.

Table 6 represents the estimated future failure rates for large, medium, and large spare parts.

**Table 6.** Failure rates and number of large, medium, and small SPs.

| | Constant Failure Rate | | | Increasing Failure Rate | | |
|---|---|---|---|---|---|---|
| **Year** | **Large SPs** | **Medium SPs** | **Small SPs** | **Large SPs** | **Medium SPs** | **Small SPs** |
| 1 | 1200 | 2850 | 11,000 | 1200 | 2850 | 11,000 |
| 2 | 1200 | 2850 | 11,000 | 1200 | 2850 | 11,000 |
| 3 | 1200 | 2850 | 11,000 | 1800 | 5700 | 13,200 |
| 4 | 1200 | 2850 | 11,000 | 3600 | 7600 | 16,500 |
| 5 | 1200 | 2850 | 11,000 | 4200 | 8550 | 18,700 |
| 6 | 1200 | 2850 | 11,000 | 5400 | 9500 | 20,900 |

Therefore, substituting in the 11 time equations corresponding to each sub-activity, we obtain the total time for each sub-activity, considering the three categories of spare parts, as shown in Table 7.

**Table 7.** Sub-activities (in minutes), considering constant and increasing failure rates.

| | **Constant Failure Rate** | | | | | | **Increasing Failure Rate** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **1** | **2** | **3** | **4** | **5** | **6** |
| Equation (10) | 384,750 | 384,750 | 384,750 | 384,750 | 384,750 | 384,750 | 384,750 | 384,750 | 499,500 | 645,000 | 731,250 | 823,500 |
| Equation (11) | 107,500 | 107,500 | 107,500 | 107,500 | 107,500 | 107,500 | 107,500 | 107,500 | 159,000 | 230,500 | 263,000 | 307,500 |
| Equation (12) | 88,500 | 88,500 | 88,500 | 88,500 | 88,500 | 88,500 | 88,500 | 88,500 | 140,300 | 195,875 | 219,175 | 251,475 |
| Equation (13) | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 207,000 | 277,000 | 314,500 | 358,000 |
| Equation (14) | 75,250 | 75,250 | 75,250 | 75,250 | 75,250 | 75,250 | 75,250 | 75,250 | 103,500 | 138,500 | 157,250 | 179,000 |
| Equation (15) | 138,500 | 138,500 | 138,500 | 138,500 | 138,500 | 138,500 | 138,500 | 138,500 | 189,000 | 241,000 | 272,500 | 304,000 |
| Equation (16) | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 207,000 | 277,000 | 314,500 | 358,000 |
| Equation (17) | 101,500 | 101,500 | 101,500 | 101,500 | 101,500 | 101,500 | 101,500 | 101,500 | 150,000 | 212,500 | 242,000 | 280,500 |
| Equation (18) | 75,250 | 75,250 | 75,250 | 75,250 | 75,250 | 75,250 | 75,250 | 75,250 | 103,500 | 138,500 | 157,250 | 179,000 |
| Equation (19) | 107,500 | 107,500 | 107,500 | 107,500 | 107,500 | 107,500 | 107,500 | 107,500 | 159,000 | 230,500 | 263,000 | 307,500 |
| Equation (20) | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 150,500 | 207,000 | 277,000 | 314,500 | 358,000 |

Once the total times of each sub-activity have been obtained, the costs of each of them can be estimated by multiplying the times by the cost capacity rates of each year. Moreover, the idle capacity of the workers is also obtained by dividing the sub-activities' total cost values by the amount of resources available for the year. For the scenario with a constant failure rate, the idle capacities exhibit a consistent value of 5.7%. Table 8 presents the expected patterns of capacity utilization in the scenario where the failure rate increases annually. It can be observed that, considering the trend in failure rates, the current capacity will be insufficient starting from year 3 if it remains constant. This highlights the need for improved treatment of component reliability during year 3 in order to address the growing demand.

**Table 8.** Total cost of sub-activities for $\lambda_{it}$ values, estimation for 6 years.

| **Period** | **Cost** | **Resources** | **Idleness** |
|---|---|---|---|
| 1 | $798,288,382 | $846,160,123 | 5.7% |
| 2 | $819,043,880 | $868,160,286 | 5.7% |
| 3 | $1,170,248,825 | $893,336,935 | −31.0% |
| 4 | $1,627,489,077 | $921,923,717 | −76.5% |
| 5 | $1,911,260,522 | $954,191,047 | −100.3% |
| 6 | $2,263,281,805 | $990,450,306 | −128.5% |

### *5.2. Cost at Risk (CaR)*

After implementing the deterministic TD-ABC model, certain parameters that exhibit variability and present significance for the analysis process can be identified. These are mainly related to the time equations for each of the activities according to Table 9. For each of the times, its probability distribution was identified, these being uniform (U), triangular (T), and normal (N).

In addition to these variables, an effective work capacity with a uniform distribution between 78% and 92.5% is taken into account.

With this information, the probability distribution of the costs per year and the probability distribution of the present value per year are estimated. The statistics for the constant failure rate are shown in Table 10, as well as the estimation of the CaR for each of the years and the Present Value Cost at Risk (PVCaR) for the analysis period with a 95% confidence. Table 11 shows the CaR and PVCaR results for an increasing failure rate. For the so-called constant rate, it can be said, considering the variation in activity times and the variation in effective work capacity, that the maximum expected cost for year one is $782,312,415, and the maximum expected cost expressed in the present value for the six years of analysis is $3,641,917,108. For the increasing rate, the maximum expected cost per year one is equal to the constant rate of $782,312,415, which remains the same during the first two years.

However, starting from year 3, the cost increases significantly compared to the constant failure due to the growth in the failure rate. The maximum expected cost expressed in the present value (PVCaR) for the increasing failure rate for the six years of analysis is $5,721,665,780.

**Table 9.** Probability distribution for each activity: uniform (U), triangular (T), and normal (N).

| | Large (Min/Batch) | Median (Min/Batch) | Small (Min/Batch) |
|---|---|---|---|
| Verify purchase order | U(8, 12) | U(13, 17) | U(28, 32) |
| Quality control | T(16, 20, 23) | T(8, 10, 15) | T(3, 5, 7) |
| Quantity control | U(14, 16) | U(14, 16) | U(22, 28) |
| Localization verification | N(10, 1) | N(10, 1) | N(10, 1) |
| Print and labeling | T(2, 5, 6) | T(2, 5, 6) | T(2, 5, 6) |
| Transfer | U(5, 11) | U(5, 11) | U(5, 11) |
| Physical revision | T(8, 10, 11) | T(8, 10, 11) | T(8, 10, 11) |
| Picking for dispatch | U(8, 17) | U(6, 12) | U(3, 6) |
| Discount inventory | N(5, 1) | N(5, 1) | N(5, 1) |
| Packaging ordering | U(17, 22) | U(5, 12) | U(2, 7) |
| Deliver for later dispatch ordering | U(7, 12) | U(7, 12) | U(7, 12) |

**Table 10.** Total costs when considering a constant failure rate.

| Years | 1 | 2 | 3 | 4 | 5 | 6 | NPV |
|---|---|---|---|---|---|---|---|
| Mean | 714,027,189 | 732,591,896 | 753,837,061 | 777,959,847 | 805,188,441 | 835,785,602 | 3,324,027,313 |
| Median | 712,350,328 | 730,871,437 | 752,066,708 | 776,132,843 | 803,297,493 | 833,822,797 | 3,316,220,986 |
| Range | 263,153,204 | 269,995,188 | 277,825,048 | 286,715,450 | 296,750,490 | 308,027,009 | 1,225,063,209 |
| Minimum | 587,578,059 | 602,855,088 | 620,337,886 | 640,188,698 | 662,595,303 | 687,773,924 | 2,735,365,749 |
| Maximum | 850,731,263 | 872,850,276 | 898,162,934 | 926,904,148 | 959,345,793 | 995,800,933 | 3,960,428,958 |
| Car or NPCaR | 782,312,415 | 802,652,537 | 825,929,461 | 852,359,204 | 882,191,776 | 915,715,063 | 3,641,917,108 |

**Table 11.** Total costs when considering an increasing failure rate.

| Years | 1 | 2 | 3 | 4 | 5 | 6 | Present Value |
|---|---|---|---|---|---|---|---|
| Mean | 714,027,189 | 732,591,896 | 1,046,048,642 | 1,452,978,196 | 1,706,077,989 | 2,019,377,841 | 5,232,105,307 |
| Median | 712,350,328 | 730,871,437 | 1,043,516,838 | 1,449,621,174 | 1,702,153,722 | 2,014,513,807 | 5,219,903,622 |
| Range | 263,153,204 | 269,995,188 | 375,282,511 | 504,883,334 | 591,899,675 | 693,220,520 | 1,838,097,289 |
| Minimum | 587,578,059 | 602,855,088 | 863,991,366 | 1,209,778,215 | 1,421,212,366 | 1,687,218,081 | 4,342,714,542 |
| Maximum | 850,731,263 | 872,850,276 | 1,239,273,877 | 1,714,661,550 | 2,013,112,041 | 2,380,438,601 | 6,180,811,831 |
| Car or PVCaR | 782,312,415 | 802,652,537 | 1,144,221,697 | 1,587,819,659 | 1,864,342,794 | 2,206,523,961 | 5,721,668,780 |

Figure 3 shows the probability distribution of cost and the calculation of CaR for constant failure. As can be seen in Figure 3, the highest expected total cost for the first year, given the variability in task execution times with a 95% confidence level, is 716,902,244, which is lower than the annual maintenance budget, indicating that the maintenance needs for the first year can be met within the organization's budget. Figure 4 presents the probability distribution of the present value of cost and the calculation of PVCaR. Figure 4 shows the present value of the cost during a 6-year analysis period, taking into account the time value of money. The maximum expected present value with a 95% confidence level is 4,409,061,788. This is an important value, as it indicates the maximum amount that the company should have in present value to meet the long-term maintenance needs of the organization. The probability distributions of cost for years 2 to 6 with constant failure and the calculation of CaR per year are presented in Appendix Figures A1–A5, respectively.

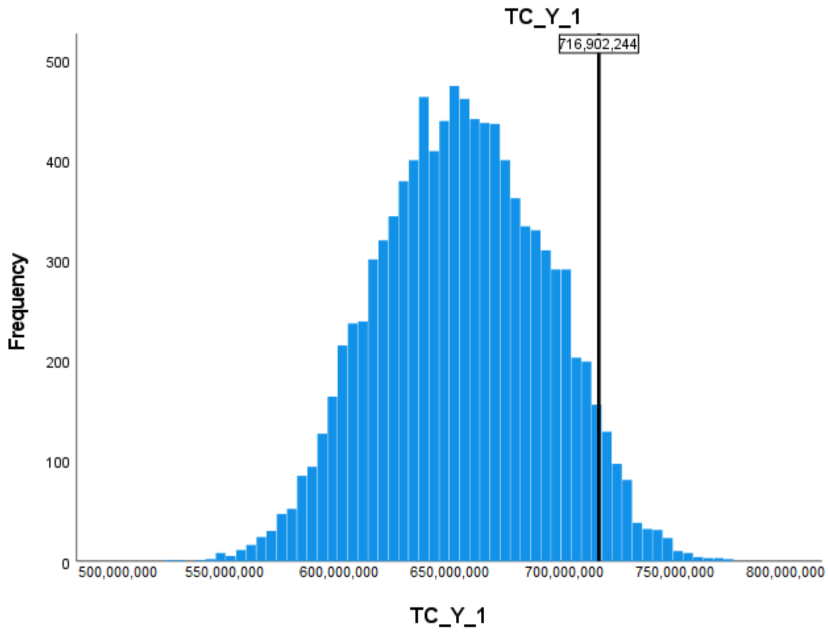



**Figure 3.** Total cost behavior for year 1 and CaR. (Mean = $6.56 \times 10^8$; Std. Dev. = 37,416,816.121; N = 10,000).

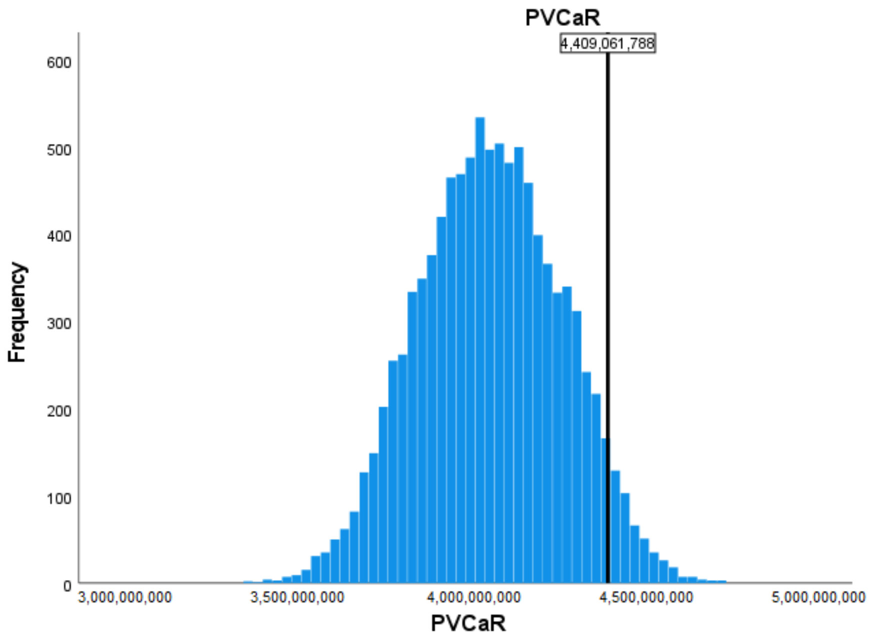



**Figure 4.** Total cost behavior for year 6 PVCaR. (Mean = $4.07 \times 10^9$; Std. Dev. = $2.062 \times 10^8$; N = 10,000).

Furthermore, the probability of allocating maintenance work can be calculated according to the resources available in each of the periods (Table 12). As can be seen, in years 1 and 2, the organization can compress more; and in year 3, there is only a 7.9% probability of committing to the works according to the budget. As for years 4, 5, and 6, the company could not carry out the activities according to the budget, so in year 3, the company should take actions to guarantee the continuity of the operation.

**Table 12.** Budget compliance (%) included the considered variability.

| | % Budget Fulfillment |
|---|---|
| Year 1 | 100.0% |
| Year 2 | 100.0% |
| Year 3 | 7.9% |
| Year 4 | 0.0% |
| Year 5 | 0.0% |
| Year 6 | 0.0% |

## 6. Discussion and Conclusions

Due to the limitations encountered in the design, implementation, and use of effective costing systems within complex organizations, more sophisticated and alternative costing systems are required. The application and development of TDABC in the field of logistics, particularly in spare parts depots, proved to be straightforward. Moreover, it can emerge as a vital tool for accurately assessing the actual costs linked to every spare parts logistics operation. Simultaneously, it proves to be well-suited for companies in the sector, as it offers the convenience of cost allocation based only on time. Therefore, adopting this methodology presents itself as a highly advantageous option.

The utilization of time equations presents itself as a considerably attractive option because it simplifies the generation of information about the efficiency of departments, processes, and activities and makes possible the development of sophisticated mathematical models and optimization approaches.

In our costing model, the set of activities related to logistics and spare parts management processes are represented within the TD-ABC matrix model, and we consider the Weibull reliability functions for each type of component, allowing for the estimation of component failure rates. By using this model, it is possible to account for the inherent variability of the costs in order to perform a proper risk analysis.

The general model and set of equations can be easily adapted to different situations and for different types of analysis. The case study presented here is particularly interesting because it offers a typical situation in spare parts management processes, highlighting the main costs and cost drivers.

After the design of the activity-based cost model linking resources, activities, and cost objects, we should consider the variability of the most relevant variables. For the analysis of the variability, we considered uniform, triangular, and normal probability distributions.

The implementation of the TDABC method for a real spare parts DC provided several managerial insights.

From the time required to carry out the activities of each spare part and the costs of the warehouse, it can be concluded that the company does not use 100% of the resources allocated to the warehouse. Through the model, it can be observed that there is a percentage of resources that are not used. It is estimated that there is a level of idle resources which approaches 19% of the capacity.

On the other hand, if we consider that component failure rates tend to increase over time, idle capacities will tend to decrease, and it will be necessary to increase resources to meet the needs of increasing volumes of activities in future years. This constitutes a predictive tool, which, when considering the reliability model, allows us to project the future behavior of costs and behavior of idle capacities.

It is important for companies to understand the need to identify, quantify, and manage the risk inherent in their activities. Proper risk management allows the company to focus on profitability objectives, guaranteeing the company's stability and solvency. In this article, a methodology for measuring risk based on the Monte Carlo simulation was proposed which allows us to obtain the results related to the maximum cost that the organization can have given its productive factors, highlighting the CaR calculation, which is a measure in the short and medium term, and PVCaR, which is a long-term measure that considers the time value of money. The proposed methodology is cost-effective, as it allows us to obtain good results at low costs in reasonable and understandable computational times for decision-makers.

We believe that the main limitation of the study is the requirement of having information on historical-failure records. Despite the advent of intelligent technologies and cyber–physical systems, many organizations possess a significant amount of data regarding the condition of equipment and its components, from which obtaining Weibull reliability coefficients can be relatively straightforward.

Further research should include the analysis of correlations between variables in indicators such as CaR and PVCaR. Additionally, there is a consideration to integrate the model with different techniques for calculating risk indicators, techniques such as fuzzy logic, decision trees, Markov modeling, and heuristic techniques such as genetic algorithms.

**Author Contributions:** Methodology, O.D. and P.A.; Formal analysis, P.A.; Investigation, O.D., V.J. and K.C.; Data curation, V.J. and K.C.; Writing—original draft, O.D.; Writing—review & editing, P.A. and V.J. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** The data are not publicly available due to privacy restrictions.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

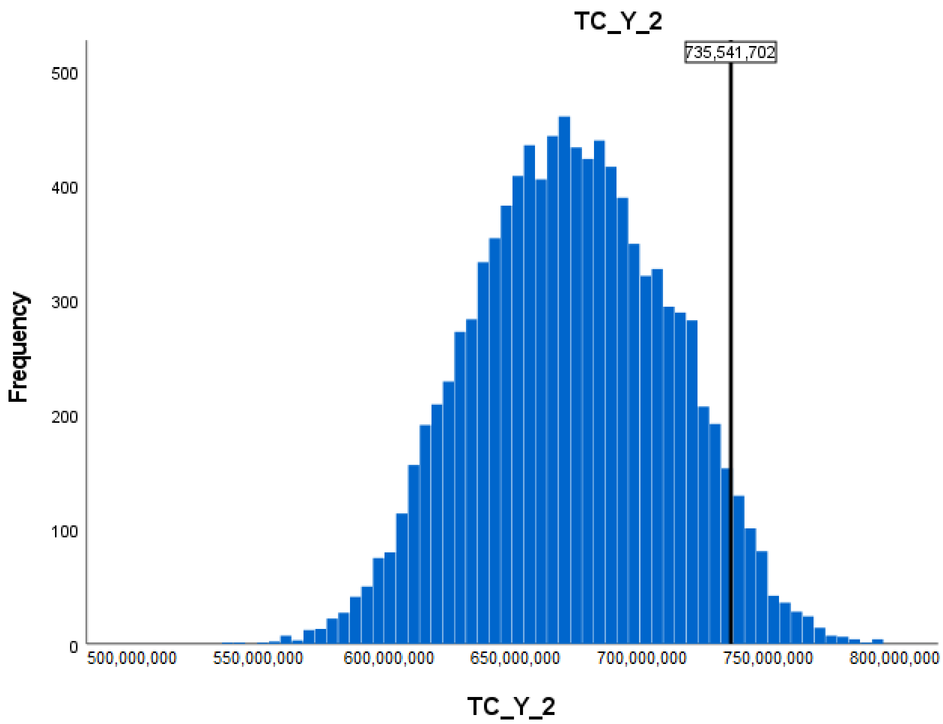



**Figure A1.** Total cost behavior for year 2 and CaR. (Mean = $6.73 \times 10^8$; Std. Dev. = 38,389,653.34; N = 10,000).

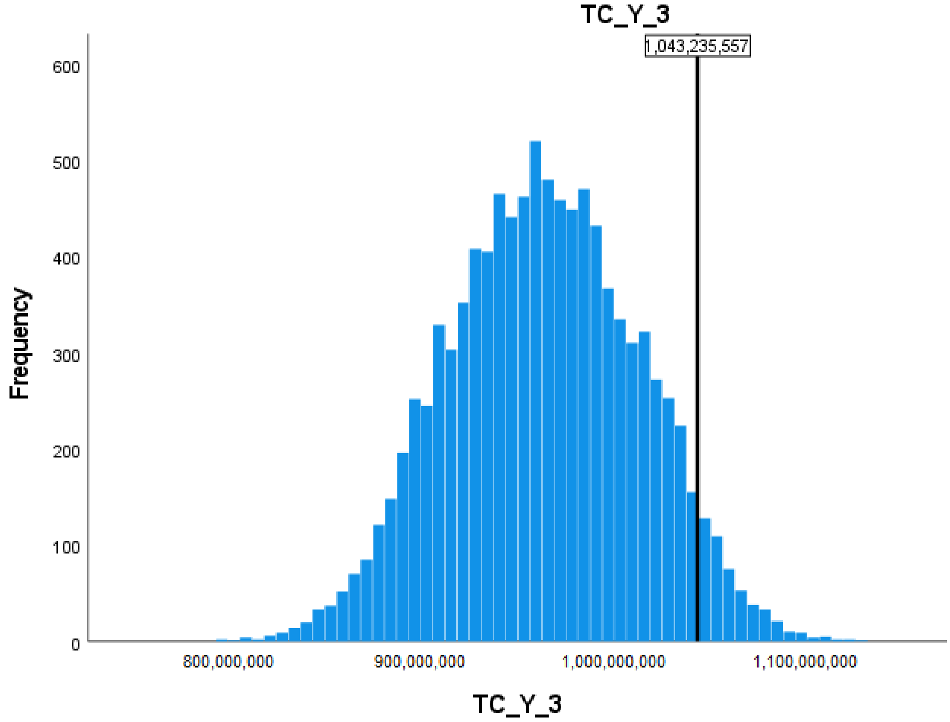



**Figure A2.** Total cost behavior for year 3 and CaR. (Mean = $9.63 \times 10^8$; Std. Dev. = 49,230,554.601; N = 10,000).

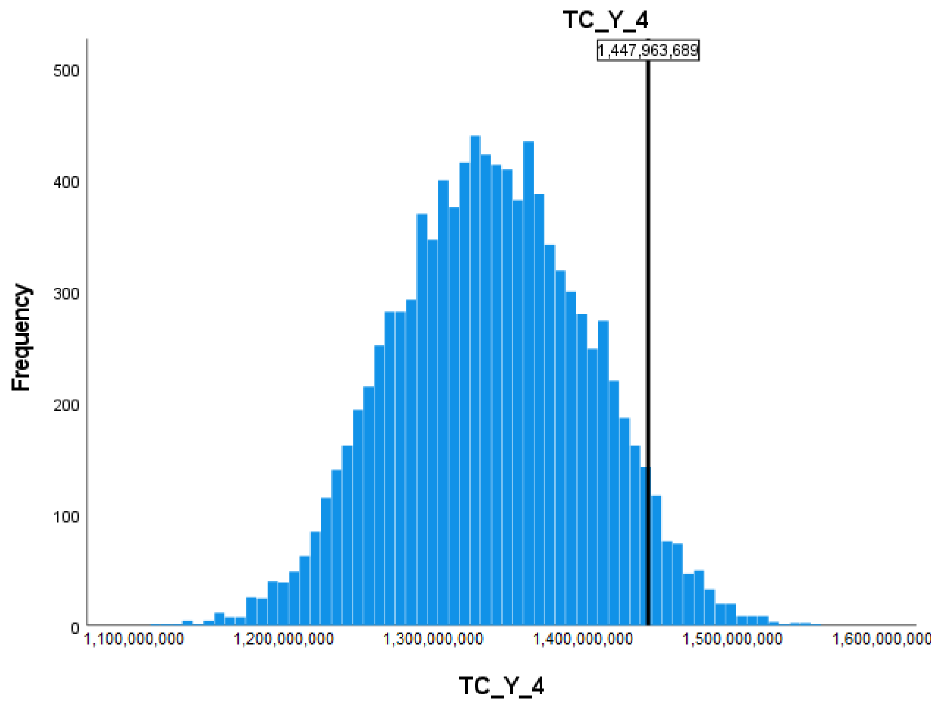



**Figure A3.** Total cost behavior for year 4 and CaR. (Mean = $1.34 \times 10^9$; Std. Dev. = 64,680,670.304; N = 10,000).

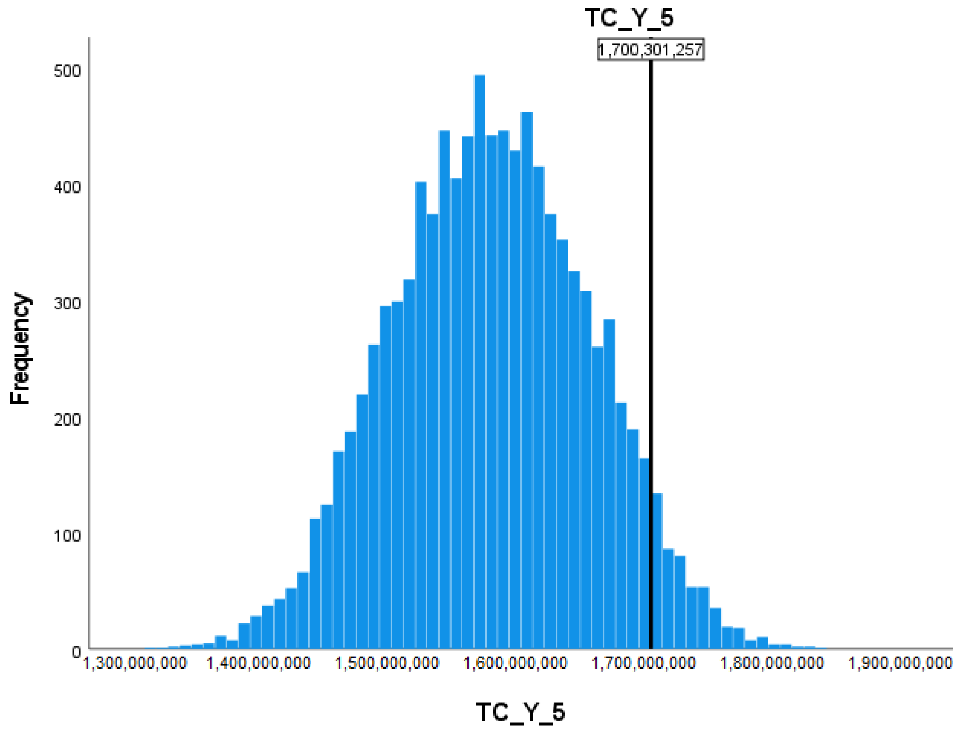



**Figure A4.** Total cost behavior for year 5 and CaR. (Mean = 1.58 $\times$ 10$^9$; Std. Dev. = 75,884,798.384; N = 10,000).

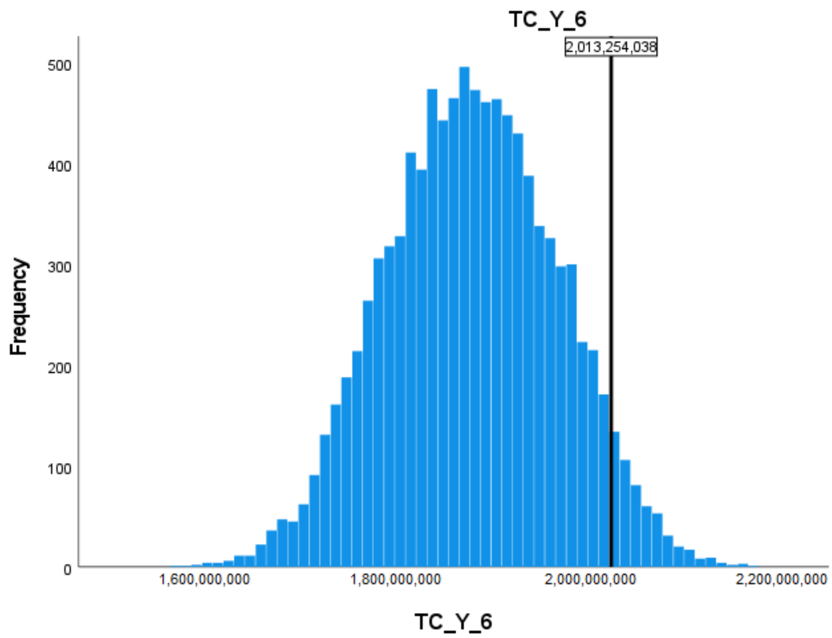



**Figure A5.** Total cost behavior for year 6 and CaR. (Mean = 1.87 $\times$ 10$^9$; Std. Dev. = 88,505,258.373; N = 10,000).

## References

1. Roda, I.; Garetti, M. Application of a performance-driven total cost of ownership (TCO) evaluation model for physical asset management. In *Value Based and Intelligent Asset Management*; Lecture Notes in Mechanical Engineering; Springer: Cham, Switzerland, 2015; ISBN 9783319155357.
2. Franciosi, C.; Iung, B.; Miranda, S.; Riemma, S. Maintenance for Sustainability in the Industry 4.0 context: A Scoping Literature Review. *IFAC-PapersOnLine* **2018**, *51*, 903–908. [CrossRef]

3. Duran, O.; Roda, I.; Macchi, M. Linking the spare parts management with the total costs of ownership: An agenda for future research. *J. Ind. Eng. Manag.* **2016**, *9*, 991–1002. [CrossRef]
4. Elbasheer, M.; Longo, F.; Mirabelli, G.; Padovano, A.; Solina, V.; Talarico, S. Integrated Prescriptive Maintenance and Production Planning: A Machine Learning Approach for the Development of an Autonomous Decision Support Agent. *IFAC-PapersOnLine* **2022**, *10*, 2605–2610. [CrossRef]
5. Ansari, F.; Glawar, R.; Nemeth, T. PriMa: A prescriptive maintenance model for cyber-physical production systems. International. *J. Comput. Integr. Manuf.* **2019**, *32*, 482–503. [CrossRef]
6. Harding, A. *Reliability, Maintenance and Logistic Support: A Life Cycle Approach*; Springer Science & Business Media: Berlin, Germany, 2002; Volume 53, ISBN 9781461371069.
7. *ISO 31000:2018*; I(en) Risk Management—Guidelines. Online Browsing Platform (OBP): London, UK, 2018.
8. van den Honert, A.F.; Schoeman, J.S.; Vlok, P.J. Correlating the content and context of PAS 55 with the ISO 55000 series. *S. Afr. J. Ind. Eng.* **2013**, *24*, 24–32. [CrossRef]
9. Hu, Q.; Bai, Y.; Zhao, J.; Cao, W. Modeling spare parts demands forecast under two-dimensional preventive maintenance policy. *Math. Probl. Eng.* **2015**, *2015*, 728241. [CrossRef]
10. Durán, O. Spare parts criticality analysis using a fuzzy AHP approach. *Tech. Gaz.* **2015**, *22*, 899–905. [CrossRef]
11. Durán, O.; Durán, P.A. Prioritization of Physical Assets for Maintenance and Production Sustainability. *Sustainability* **2019**, *11*, 4296. [CrossRef]
12. Márquez, A.C.; Macchi, M.; Parlikad, A.K. (Eds.) *Value Based and Intelligent Asset Management: Mastering the Asset Management Transformation in Industrial Plants and Infrastructures*; Springer: Berlin/Heidelberg, Germany, 2019.
13. *ISO 55000:2014*; Asset Management—Overview, Principles and Terminology. International Organization of Standardisation: Geneva, Switzerland, 2014.
14. Kaplan, R.S. Improving value with TDABC. *Healthc. Financ. Manag.* **2014**, *68*, 76–84.
15. Jiménez, V.; Afonso, P. Risk Assessment in Costing Systems Using Costing at Risk (CaR): An Application to the Coffee Production Cost. In Proceedings of the 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bali, Indonesia, 4–7 December 2016; pp. 1315–1319.
16. Korpi, E.; Ala-Risku, T. Life cycle costing: A review of published case studies. *Manag. Audit. J.* **2008**, *23*, 240–261.
17. Zachariassen, F.; Arlbjørn, J.S. Exploring a differentiated approach to total cost of ownership. *Ind. Manag. Data Syst.* **2011**, *111*, 448–469. [CrossRef]
18. Maisenbacher, S.; Klöppel, M.; Laubmann, J.; Behncke, F.; Mörtl, M. Integrated Value Engineering: Consideration of Total Cost of Ownership for Better Concept Decision. In Proceedings of the 2016 Portland International Conference on Management of Engineering and Technology (PICMET), Honolulu, HI, USA, 4–8 September 2016; pp. 623–632.
19. Woodhouse, J. What is the value of asset management? *Infrastruct. Asset Manag.* **2019**, *6*, 102–108. [CrossRef]
20. *IEC 60300–3-3:2017*; Dependability Management–Part 3–3: Application Guide–Life Cycle Costing. International Electrotechnical Commission: Geneva, Switzerland, 2017.
21. *ISO 15663-1:2000*; International Standard Petroleum and Natural Gas Industries-Life Cycle Costing Part 1: Methodology. ISO: London, UK, 2000.
22. *SEMI E35-0618*; SEMI International Standards. Guide to Calculate Cost of Ownership (COO) Metrics for Semiconductor Manufacturing Equipment. SEMI International Standard Brussels: Brussels, Belgium, 2018.
23. *ICS Code: 91.010.20*; Standard Practice for Measuring Life-Cycle Costs of Buildings and Building Systems. ASTM: West Conshohoken, PA, USA, 2017; p. 23. [CrossRef]
24. *ISO 15686:2008*; Buildings and Constructed Assets—Service-Life Planning—Part 5: Life Cycle Costing. International Organization for Standardization: Geneva, Switzerland, 2008.
25. *APPA 1000-1*; Total Cost of Ownership for Facilities Asset Management (TCO)—Part 1: Key Principles. APPA: Stanford, CT, USA, December 2017; p. 100, ISBN 1-890956-97-X.
26. *AC/327*; NATO Guidance on Life Cycle Costs. ALCCP1: Brussels, Belgium, 2018.
27. Cooper, R.; Kaplan, R.S. Profit Priorities from Aotivity-Based Costing. *Harv. Bus. Rev.* **1991**, *69*, 130–135.
28. Rodriguez Rivero, E.J.; Emblemsvag, J. Activity-based life-cycle costing in long-range planning. *Rev. Account. Financ.* **2007**, *6*, 370–390. [CrossRef]
29. Emblemsvag, J.; Emblemsva, J. Activity-based life-cycle costing. *Manag. Audit. J.* **2007**, *16*, 17–27. [CrossRef]
30. Knights, P.F. Best-In-Class maintenance benchmarks in Chilean open—Pit mines. *CIM Bull.* **2005**, *98*, 93.
31. March, S.T.; Smith, G.F. Design and natural science research on information technology. *Decis. Support Syst.* **1995**, *15*, 251–266. [CrossRef]
32. Mo, J.; Wang, L.; Qiu, Z.; Shi, Q. A nonprobabilistic structural damage identification approach based on orthogonal polynomial expansion and interval mathematics. *Struct. Control Health Monit.* **2019**, *26*, e2378. [CrossRef]
33. Hazır, Ö.; Ulusoy, G. A classification and review of approaches and methods for modeling uncertainty in projects. *Int. J. Prod. Econ.* **2020**, *223*, 107522. [CrossRef]
34. Oehmen, J.; Locatelli, G.; Wied, M.; Willumsen, P. Risk, uncertainty, ignorance and myopia: Their managerial implications for B2B firms. *Ind. Mark. Manag.* **2020**, *88*, 330–338. [CrossRef]

35. Nachtmann, H.; Needy, K.L. Methods for handling uncertainty in activity based costing systems. *Eng. Econ.* **2003**, *48*, 259–282. [CrossRef]
36. Bi, H.; Lu, F.; Duan, S.; Huang, M.; Zhu, J.; Liu, M. Two-level principal–agent model for schedule risk control of IT outsourcing project based on genetic algorithm. *Eng. Appl. Artif. Intell.* **2020**, *91*, 103584. [CrossRef]
37. Jiang, C.; Xu, R.; Wang, P. Measuring effectiveness of movement-based three-way decision using fuzzy Markov model. *Int. J. Approx. Reason.* **2023**, *152*, 456–469. [CrossRef]
38. Jiao, L.; Yang, H.; Liu, Z.G.; Pan, Q. Interpretable fuzzy clustering using unsupervised fuzzy decision trees. *Inf. Sci.* **2022**, *611*, 540–563. [CrossRef]
39. Liu, W.; Lai, Z.; Bacsa, K.; Chatzi, E. Physics-guided Deep Markov Models for learning nonlinear dynamical systems with uncertainty. *Mech. Syst. Signal Process.* **2022**, *178*, 109276. [CrossRef]
40. Nguyen, T.; Duong, Q.H.; Nguyen, T.; Van Zhu, Y.; Zhou, L. Knowledge mapping of digital twin and physical internet in Supply Chain Management: A systematic literature review. *Int. J. Prod. Econ.* **2022**, *244*, 108381. [CrossRef]
41. Wang, J.; Wang, Y.; Zhang, Y.; Liu, Y.; Shi, C. Life cycle dynamic sustainability maintenance strategy optimization of fly ash RC beam based on Monte Carlo simulation. *J. Clean. Prod.* **2022**, *351*, 131337. [CrossRef]
42. Díaz, H.; Teixeira, A.P.; Soares, C. Application of Monte Carlo and Fuzzy Analytic Hierarchy Processes for ranking floating wind farm locations. *Ocean Eng.* **2022**, *245*, 110453. [CrossRef]
43. Durán, O.; Afonso, P. Physical Asset Risk Management. In *Risk Management: An Overview*; Nova Science Publishers, Inc.: Hauppauge, NY, USA, 2021; pp. 45–82.
44. Durán, O.; Afonso, P.S.; Durán, P.A. Spare parts cost management for long-term economic sustainability: Using fuzzy activity based LCC. *Sustainability* **2019**, *11*, 1835. [CrossRef]
45. Jiménez, V.; Duarte, C.; Afonso, P. Cost System Under Uncertainty: A Case Study in the Imaging Area of a Hospital. In *Enhancing Synergies in a Collaborative Environment*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 325–333.
46. Kropivšek, J.; Jošt, M.; Grošelj, P.; Kitek Kuzman, M.; Kariž, M.; Merela, M.; Gornik Bučar, D. Innovative model of the cost price calculation of products from invasive non-native wood species based on the FTDABC method. *Forests* **2021**, *12*, 1519. [CrossRef]
47. Ostadi, B.; Mokhtarian Daloie, R.; Sepehri, M. A combined modeling of fuzzy logic and Time-Driven Activity-based Costing (TDABC) for hospital services costing under uncertainty. *J. Biomed. Inform.* **2019**, *89*, 11–28. [CrossRef]
48. Rondeau, M.; Arès, R. On the Test Particle Monte-Carlo method to solve the steady state Boltzmann equation, the congruity of its results with experiments and its potential for shared memory parallelism. *J. Comput. Phys.* **2021**, *444*, 110590. [CrossRef]
49. Zadeh, L.; Aliev, R. *Fuzzy Logic Theory and Applications: Part I and Part II*; World Scientific Publishing: Singapore, 2018.
50. de Soto, A.R.; Sobrino, A.; Trillas, E.; Alsina, C. Reflections on an old problem: That of preserving the logical forms and symmetry. *Fuzzy Sets Syst.* **2020**, *401*, 150–162. [CrossRef]
51. Sarokolaei, M.A.; Bahreini, M.; Bezenjani, F.P. Fuzzy Performance Focused Activity based Costing (PFABC). *Procedia-Soc. Behav. Sci.* **2013**, *75*, 346–352. [CrossRef]
52. Durán, O.; Carrasco, A.; Afonso, P.S.; Durán, P.A. Evolutionary optimization of spare parts inventory policies: A life cycle costing perspective. *IFAC-PapersOnLine* **2019**, *52*, 2243–2248. [CrossRef]
53. Edjossan-Sossou, A.M.; Galvez, D.; Deck, O.; Al Heib, M.; Verdel, T.; Dupont, L.; Chery, O.; Camargo, M.; Morel, L. Sustainable risk management strategy selection using a fuzzy multi-criteria decision approach. *Int. J. Disaster Risk Reduct.* **2020**, *45*, 101474. [CrossRef]
54. Ökten, G.; Liu, Y. Randomized quasi-Monte Carlo methods in global sensitivity analysis. *Reliab. Eng. Syst. Saf.* **2021**, *210*, 107520. [CrossRef]
55. Hu, X.; Chen, X.; Parks, G.T.; Yao, W. Review of improved Monte Carlo methods in uncertainty-based design optimization for aerospace vehicles. *Prog. Aerosp. Sci.* **2016**, *86*, 20–27. [CrossRef]
56. Costa, T.M.; Chalco-Cano, Y.; Román-Flores, H. Wirtinger-type integral inequalities for interval-valued functions. *Fuzzy Sets Syst.* **2020**, *396*, 102–114. [CrossRef]
57. Ali Elfarra, M.; Kaya, M. Estimation of electricity cost of wind energy using Monte Carlo simulations based on nonparametric and parametric probability density functions. *Alex. Eng. J.* **2021**, *60*, 3631–3640. [CrossRef]
58. Touran, A.; Wiser, E.P. Monte Carlo technique with correlated random variables. *J. Constr. Eng. Manag.* **1992**, *118*, 258–272. [CrossRef]
59. Zhaodong, H.; Rongxuan, L.; Jing, J. Development and Production Costs Estimating for Aviation Equipment Based on Uncertainty Design. *Procedia Eng.* **2015**, *99*, 143–149. [CrossRef]
60. van Aken, J.; Chandrasekaran, A.; Halman, J. Conducting and publishing design science research: Inaugural essay of the design science department of the Journal of Operations Management. *J. Oper. Manag.* **2016**, *48*, 1–8. [CrossRef]
61. Hevner, A.R.; March, S.T.; Park, J.; Ram, S. Design science in information systems research. *Manag. Inf. Syst. Q.* **2004**, *28*, 75–105. [CrossRef]
62. Baskerville, R.L.; Kaul, M.; Storey, V.C. Genres of inquiry in design-science research: Justification and evaluation of knowledge production. *Manag. Inf. Syst. Q.* **2015**, *39*, 541–564. [CrossRef]
63. Afonso, P.S.; Paisana, A.M. An Algorithm for Activity Based Costing based on Matrix Multiplication. In Proceedings of the 2009 IEEE International Conference on Industrial Engineering and Engineering Management, Hong Kong, China, 8–11 December 2009; pp. 920–924.

64. Lai, C.D.; Murthy, D.N.P.; Xie, M. Weibull distributions. *Wiley Interdiscip. Rev. Comput. Stat.* **2011**, *3*, 282–287. [CrossRef]
65. Chen, T. A Dynamic Failure Rate Forecasting Model for Service Parts Inventory. *Sustainability* **2018**, *10*, 2408. [CrossRef]