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" Mathematical Model for the Optimal Determination of the Recovery Time Objective (RTO) in Business Continuity Systems "

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ABSTRACT: *The definition of an optimal Recovery Time Objective (RTO) is a critical element of Business Continuity Management (BCM), as it allows organizations to balance recovery costs with the need to quickly restore critical operations. This article proposes a model based on quantitative methods, such as the Analytic Hierarchy Process (AHP), to determine an optimal and acceptable RTO, integrating the analysis of financial and operational impact. Additionally, the model includes a statistical approach to verify compliance between observed and target RTO. The results can guide organizations toward more effective strategic decisions in terms of resilience and operational continuity.*

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I. INTRODUCTION

The recent past highlights how crucial it is to have models and frameworks capable of ensuring the functionality of essential services, which are the pillars of modern society. This necessity becomes evident when adverse events compromise critical infrastructures, as demonstrated in the literature [1]. Transport, communications, finance, energy, food, and water supply are just some of the infrastructures that may exhibit poor resilience in the event of a failure.

In response to these vulnerabilities, organizations are adopting management models that promote a "culture of resilience," integrating tools such as Business Continuity Management (BCM). This system addresses inefficiencies through structured approaches to reduce risks and mitigate the effects of crises [20]. Among the key elements of BCM, the use of the Business Impact Analysis (BIA) model stands out, which is essential for identifying critical functions, required resources, and optimal recovery times.

The primary objective of this work is to propose a calculation model for determining the maximum tolerable downtime (RTO), a crucial metric for establishing recovery priorities and resource allocation. The model is designed to address strategic questions: how to optimize the RTO based on the criticality of business processes? What are the best methods to verify its application? And what metrics can evaluate the effectiveness of a Business Recovery Plan?

The structure of the study focuses on three main areas: (1) an overview of BCM and its practical applications; (2) a detailed presentation of the proposed model for calculating the optimal RTO and analyzing its financial impact; (3) a practical demonstration of the model with conclusions on its future implications.

II. LITTERATURE REVIEW

In the last two decades, the importance of Business Continuity Management models has grown, especially with the emergence of e-business. Several authors have considered BC and BCM as part of organizational management and organizational strategy [2]. According to ISO 22301 (2019), the BCM process is a structured model that includes operational planning, BIA, continuity strategies, policy implementation, and testing. [3] emphasizes that models developed over time show how BCM is essential for building resilience and responding to critical events. In particular, [4] defined BCM as “a management process that identifies potential threats to an organization and provides a framework for building resilience and the capacity for an effective response.”

Authors such as Torabi et al. (2016) [5] and Revilla et al. (2017) [6] have presented mathematical and statistical methods that integrate BCM with advanced risk analysis techniques. Particularly noteworthy is the model developed by Samantra et al. (2014) [7], which uses fuzzy theory to convert qualitative data into numerical parameters, thus improving risk assessment. The model consists of four main phases: risk identification, collection of linguistic data from experts, calculation of risk impact, and development of action plans. Specifically, the authors proposed a model composed of four main phases: (1) identification of risks in the context of information technology outsourcing, (2) collection of aggregated linguistic data on the probability and impact of risks from expert opinions, (3) calculation of the impact of each risk by multiplying the likelihood of occurrence by its related impact, and (4) the development of mitigation strategies.

The integration of Business Impact Analysis into the risk assessment framework has also been studied by Aghabegloo et al. (2024) [8], who proposed a decision-making model to analyze asset criticalities through a framework where Business Impact Analysis is linked to a BWM-TOPSIS methodology to assist decision-makers in the process of analyzing critical assets. The authors use Business Impact Analysis to identify assets considered strategic. This assessment, derived from Păunescu et al. (2018) [9], was modified by the authors considering the specific criticalities of the examined sector, namely the petrochemical industry, where there is a dependence on certain products that are essential for the smooth operation of processes (Tsay et al., 2018) [10]. For this reason, the authors focus in their study not only on the correct understanding of the processes underlying a given organization but also on all the elements that contribute to ensuring their efficiency.

In the context of BCM, studies on so-called “resilient maintenance” of critical assets are also very important. In this regard, Sun et al. (2022) [16] demonstrated that the implementation of preventive maintenance systems helps avoid failures and machine downtime, thus protecting the organization from unforeseen interruptions. Obviously, the implementation of such preventive systems must be supported by cost monitoring systems that help organizations optimize assets while coordinating them with operational costs. For this purpose, the authors propose a method to determine the optimal labor cost based on the minimum acceptable resilience level (MARL) and the maximum acceptable recovery time (MART).

Similarly, Zeng et al. (2017) [11] propose an approach that integrates operational recovery into the preventive risk framework, structured into a four-phase model: protection, mitigation, emergency, and recovery. Another significant contribution comes from Shafiee's FANP model (2015) [12], which uses fuzzy analysis to select risk mitigation strategies in the renewable energy sector. This model demonstrates how comparison criteria such as safety, added value, cost, and feasibility can guide strategic decisions.

The creation of resilient supply chains has also been a topic of study in recent academic literature. Sureeyatanapas et al. (2020) [13] demonstrated that, when disruptive events occur, it is crucial to create a resilient logistics chain to withstand potential setbacks. Particularly important is the selection of suppliers, taking into account their resilience capacity in the face of adverse events. For this reason, a hybrid analysis model was developed that, using the TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution), helps organizations in the supplier selection process, ensuring a good level of management of various forms of uncertain and incomplete data that tend to reduce the quality of supplier performance evaluation. Along the same lines, Leong et al. (2022) [14] proposed a hybrid method for selecting main suppliers based on the combined use of GRA, BWM, and TOPSIS methods. Specifically, the authors used the GRA method to determine the importance levels of different criteria, the BWM for determining the weights of the criteria, and the TOPSIS method to evaluate supplier performance.

Finally, Merz et al. (2009) [15] developed a multicriteria decision-making system to plan the operational continuity of critical infrastructures. This model, based on MCDA methods, allows for the prioritization of Business Continuity Planning measures, demonstrating how a systematic and quantitative approach can strengthen organizational resilience.

To summarize the analysis of the existing literature, the following table describes the selected models, which have been considered as the basis for the development of the model proposed in this study.

Table 1: Summary of the most important models in the literature

Authors	Year	Topic/Contribution	References to Models
Aghabegloo et al.	2024	BWM-TOPSIS for analysis and selection of critical assets.	Decision-making model to integrate BIA and risk analysis.
Sun et al.	2022	Preventive maintenance to avoid failures and machine downtime, integrated with cost monitoring.	Method based on MARL and MART to balance costs and resilience.
Leong et al.	2022	Hybrid method (GRA, BWM, TOPSIS) for selecting main suppliers.	Hybrid model for supplier evaluation and selection based on multiple criteria and weights.

Sureeyatanapas et al.	2020	Creation of resilient supply chains using the TOPSIS method for supplier selection.	Hybrid model for managing uncertain data in supplier selection.
Păunescu et al.	2018	Evaluation of critical assets in the petrochemical sector.	Method to identify strategic elements in business processes.
Revilla et al.	2017	Effectiveness of quantitative approaches in BCM management.	Statistical methods applied to BCM.
Zeng et al.	2017	Approach to integrate operational recovery and risk assessment.	Four-phase model: protection, mitigation, emergency, and recovery.
Torabi et al.	2016	Use of mathematical/statistical methods to integrate BCM with risk analysis techniques.	Quantitative models based on risk analysis.
Shafiee	2015	Fuzzy analysis to select risk mitigation strategies in renewable energy.	FANP model to select the best strategy based on criteria of safety, cost, value, and feasibility.
Samantra et al.	2014	Fuzzy model to assess risks in the context of IT outsourcing.	Fuzzy model with four main phases for risk analysis.
Herbane	2010	Importance of BCM for building resilience and responding to critical events.	General models for resilience.
Merz et al.	2009	Multicriteria decision-making system for operational continuity planning.	MCDA method for prioritizing Business Continuity Planning measures.

III. MATERIALS & METHOD

The proposed methodology focuses on an integrated approach to determine an optimal and acceptable Recovery Time Objective (RTO). The process involves the systematic analysis of factors that influence the recovery of business activities, with particular attention to financial, operational, and reputational impacts. The methodology is structured into several phases, describing in detail the techniques and tools used. The proposed model can be summarized according to the following main points

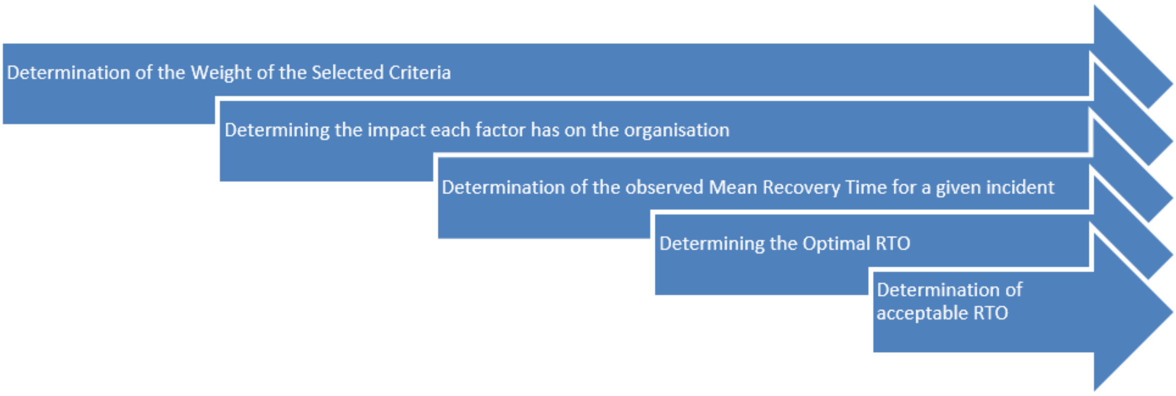

Figure 1: Graphical representation of the proposed framework

IDENTIFICATION OF CRITERIA AND IMPACT ANALYSIS

To ensure an accurate analysis, the first step is to identify the key criteria that influence recovery time. Three critical areas have been identified. The first, financial impact, assesses the economic loss the organization incurs for each hour of downtime. This parameter is crucial for evaluating the economic sustainability of prolonged disruptions. The second, operational impact, reflects the consequences on production efficiency and service delivery. Finally, the reputational impact measures the effects on how stakeholders (customers, investors, and partners) perceive the organization. For each criterion, the severity of the impact is assessed using a scale from 1 to 9, where 1 represents a negligible impact, and 9 represents a critical impact. This evaluation allows for a systematic and objective quantification of the effects of disruption.

THE ANALYTIC HIERARCHY PROCESS (AHP)

At the core of the methodology lies the use of the Analytic Hierarchy Process (AHP), a decision-making technique that facilitates the evaluation of multiple criteria. Introduced by Thomas Saaty [17-18], AHP is particularly useful for addressing complex problems, as it enables their decomposition into a hierarchy of interconnected elements. The choice to adopt this model stems from the literature, which highlights several benefits of implementing AHP, making it easier to construct an analysis framework. First, the AHP model allows qualitative judgments to be translated into quantitative data, enabling the assignment of numerical values to preferences for each criterion and alternative. Due to its ability to segregate data—breaking down complex decisions into simpler problems—the AHP model is far more versatile than other multi-decision criteria and can be adapted to a wide range of decision-making contexts. Finally, the AHP method includes a consistency check system, which helps identify and correct inconsistencies in preferences. This ensures a ranking of alternatives based on assigned weights, providing a clear and structured result that facilitates the identification of the optimal alternative. With these premises in mind, the procedure used to construct the AHP method within the proposed model is outlined below. To determine the optimal RTO value, the first step involves determining the weights of the three identified criteria (financial, operational, and reputational impacts) through the construction of a pairwise comparison matrix of the type:

$$A = \begin{bmatrix} 1 & a_{12} & a_{13} \\ \frac{1}{a_{12}} & 1 & a_{23} \\ \frac{1}{a_{13}} & \frac{1}{a_{23}} & 1 \end{bmatrix} (1)$$

Where a_{ij} represents the relative importance of criterion C_i compared to C_j. The values of a_{ij} are selected from Saaty's scale, ranging from 1 (equal importance) to 9 (absolute importance of one criterion over another). This step generates a square matrix, known as the pairwise comparison matrix, in which each element represents the relative weight between two criteria. Subsequently, the AHP model requires determining the weights of the identified criteria. To achieve this, the so-called normalized matrix is constructed using the following relations:

$$\sum_{i=1}^{n} v_i(A_j) = 1 \quad con\ j = 1,,,n \quad (2)$$

with n identifying the number of alternatives or elements compared. Each element of sum (2) is worth:

$$v_j(A_j) = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad con\ j = 1,,,n \ (3)$$

This implies that the vector of priorities of a generic alternative 'i', connected to the importance criterion, can be defined by the following relation

$$v_k = (A_i) = \sum_{j=1}^{n} \frac{v_j(A_i)}{n} \quad con\ i = 1,\dots,n \ (4)$$

To determine the importance weights of the factors in a square matrix 'A', it is necessary to calculate the sum of each element a_{ij} per column. Next, a new MRW matrix is constructed, in which each element a_{ij} represents the relative weight of an element in the column with respect to the sum of the elements in the same column. This is obtained by dividing each element a_{ij} of the matrix 'A' by the sum of the elements of the corresponding column. Finally, in the MRW matrix, the weighted arithmetic mean of the elements in each row provides the relative weight (RWR) associated with each element in the 'A' matrix. To ensure the validity of the calculations and evaluations, the AHP methodology includes a consistency analysis of the processed data. Since the MMM matrix is a reciprocal matrix, the adequacy of the experts' decisions can be confirmed by verifying the consistency of all comparisons made.

$$a_{ij} \times a_{jk} = a_{ik} \quad \forall i,j,k \ (5)$$

According to this protocol, the "A" matrix would be consistent. Considering n as the number of elements, λ_{max} the maximum eigenvalue of the 'A' matrix, and 'w' the vector of priorities, the consistency of the opinions expressed by the experts occurs when:

$$\lambda_{max} = n \ \&\ a_{ij} = \frac{w_i}{w_j} \ (6)$$

However, considering that a certain degree of inconsistency is almost always present, this can be quantified by observing that the closer the value of λ_{max} is to n, the greater the consistency of opinions. Saaty (2008)[17] showed that, for a matrix 'A' such as the one described above, it is necessary to find a vector www that satisfies the equation $A_w = \lambda_{max}$' In order to obtain the relative eigenvector, it is necessary to calculate:

$\lambda_{max} = \frac{1}{n}\sum_{I=1}^{N} v_i \frac{[A_w]_i}{w_j}$ (7)

It is important to note that small variations in the values a_{ij} lead to corresponding variations in λ_{max}. The deviation of $\lambda_{max}$with respect to n (the order of the matrix) is considered a measure of consistency. Accordingly, λ_{max}makes it possible to assess how close the scale proposed by Saaty (2003) [18] is to the ratio scale that would be used if the matrix 'A' were completely consistent. This assessment is made by means of a consistency index (CI). According to Theorem 1 of Saaty (2003) [18], the matrix 'A' is consistent if and only if λ_{max}≥ n . In other words, if the matrix 'A' is consistent, then the degree of perturbation of the matrix can be measured by calculating the ratio:

$CI = \frac{(\lambda_{max}-n)}{(n-1)}$ (8)

The CI (Coherence Index) will have a value of less than 0.1 (Saaty and Vargas, 2012) [19]. To address issues related to the consistency of matrix data, Saaty proposes the calculation of a Consistency Ratio (CR), determined through the equation:

$CR = \frac{CI}{RI}$ (9)

The CI represents the Coherence Index, calculated using the equation described above. The RI element, on the other hand, is a Random Coherence Index, determined for square matrices of order *"*n*"* by the Oak Ridge National Laboratory in the United States, and shown in Table 1 (Saaty and Vargas, 2012) [19].

Table 2: Random Consistency Index (Saaty & Vargas, 2012)

N	1	2	3	4	5	6	7	8	9	10
Random consistency index (R.I.)	0	0	0,52	0,89	1,11	1,25	1,35	1,40	1,45	1,49

A high CR value indicates greater inconsistency. For n=1or n=2, the CR is zero; for n=3, the CR should be less than 0.05; and for n=4, it should be less than 0.08. In general, for n>4, an inconsistency is considered acceptable if the CR is less than or equal to 0.10. If it exceeds this threshold, the problem must be analysed and the judgements revised. The AHP methodology also includes a consistency index applicable to the entire hierarchy. An inconsistency of 10% or less indicates that the required adjustments are minimal compared to the actual values of the elements of the eigenvectors (Saaty and Vargas, 2012) [19].

CALCULATION OF OPTIMAL RTO AND ACCEPTABLE RTO

The following relationship was used to determine the optimal Recovery Time Objective (RTO):

$RTO = \frac{\sum_{i=1}^{n}(Impact_i \times Weight_i)}{TTR}$ (10)

Where the $Impact_i$ represents the impact, determined according to a scale ranging from 1 to 9 depending on the severity, of each factor, the $Weight_i$is the coefficient representing the relative importance of each impact determined by the AHP method while TTR Time to Recover is the system's recovery capability. In the proposed model, the TTR represents the actual RTO value and is determined by taking into account the average value of the historical series of recovery times for each failure examined observed in the organisation or sector where the former are not available. Once the optimal value has been determined, the RTO value deemed acceptable for the organization is then determined. This will be determined taking into account that for each RTO there is an impact/damage $D(t)$ which is modelled according to a function that grows linearly over time:

$D(t) = k \times t$ (11)

Assuming 'S' the acceptable threshold value, which in our case is the previously determined optimal RTO value, 0 the time at which the interruption due to the event occurs, and 'T' the time required for recovery, the acceptable RTO value will be determined as the definite integral of the function $D(t)$. In other words:

$D(t) = \int_0^T k \times t\,dt$ (12)

Developing the definite integral we have the following relationship

$D(t) = \int_0^T k \times t\,dt = k \times \left[\frac{t^2}{2}\right]_o^T = k \times \left[\frac{T^2}{2}\right]$ (13)

From which we obtain:

$k \times \frac{T^2}{2} = S$ (14)

Solving equation (14) for T will give us

$T^2 = \frac{2S}{k} \rightarrow T = \sqrt{\frac{2S}{k}}$ (15)

$\sqrt{\frac{2S}{k}}$ represents the value of the RTO acceptable to the organization.

COMPARISON OF ACCEPTABLE RTO AND ACTUAL RTO

What is determined with equations (10) and (15) will then need to be compared with the actual RTO observed at the organization. The objective at this stage is to check whether the actual RTO value is in line with the RTO value deemed acceptable for the organization. Assuming that the data population follows a normal distribution, the model was supplemented with a Student's t-test in order to test the following hypotheses. The null hypothesis (H_0) that the observed mean recovery time is equal to the defined RTO. In other words, there is no significant difference between the target RTO and the observed mean recovery time, and the alternative hypothesis (H_1) according to which the observed mean recovery time is different from the defined RTO (this can be tested as a major or minor difference, depending on the type of test).

DETERMINATION OF FINANCIAL IMPACT

The final element of the proposed model is the determination of the financial impact linked to the RTO value determined above. At this stage, the following parameters are taken into account: TTR Time to Recover i.e. system recovery capacity or actual RTO; (μ_{Target}; δ_{Target})) mean value and mean square deviation of the target RTO values and $D(h)$ financial loss per hour of downtime. Assuming that the RTO follows a normal distribution, we will calculate the probability $P(X \leq x)$) of incurring a certain financial loss per downtime hour by applying the probability density function of a normal distribution

$f(x) = \frac{1}{\delta\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\delta^2}}$ (16)

The variation of productivity versus day time at different solar intensities at constant Spherical dome heights 10, 18 and 40 as shows in figures 9, 10 and 11 respectively.

IV. CASE STUDY

In the presented case study, two different types of failures may occur within a given organization. The first incident has a significant impact on the company's operations and also causes financial and reputational distress. The second incident, although it does not affect operations or reputation among stakeholders, has significant financial repercussions. The objective is to estimate an RTO value for both incidents that is economically acceptable to the company. Following the model and considering that the incidents impact financial, operational, and reputational aspects, the organization, using the AHP method, will determine the weight of each criterion. To construct the pairwise comparison matrix, the organization will apply the scale of values proposed by Saaty

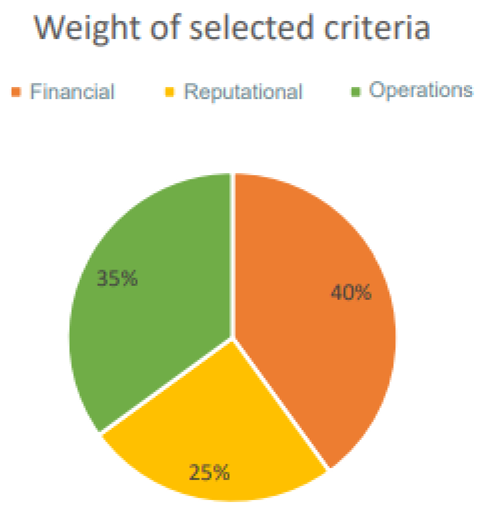

Figure 2: Weight of Selected Criteria

Fig. 2 shows the relative importance of the three criteria (financial, operational, and reputational) in determining the Recovery Time Objective (RTO). As seen, the financial criterion carries the highest weight (40%), suggesting that the economic impact is prioritized in the analysis. This is followed by the operational criterion (35%), reflecting the need to restore internal functionality. The reputational criterion holds a lower weight (25%) but remains relevant for strategic decisions. This graph is presented alongside the distribution of acceptable CR values (Fig. 3), which illustrates how the distribution of the CR consistency ratio values compares to the acceptable thresholds.

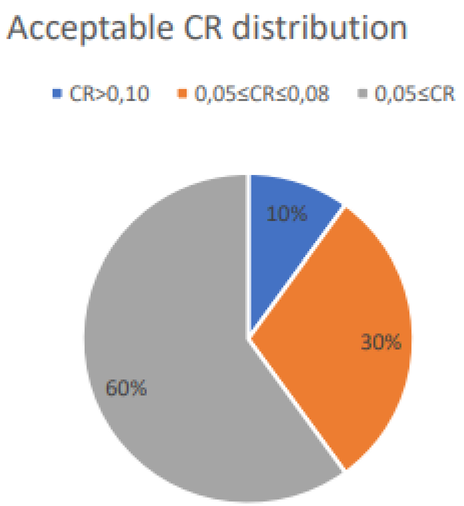

Figure 3: Acceptable CR distribution

As shown, the majority of CR values (60%) fall within the acceptable threshold $CR \leq 0.05$, ensuring good consistency in decision-making. A moderate portion (30%) falls within the acceptable but higher range ($0.05 < CR \leq 0.08$). Only 10% show inconsistencies ($CR > 0.10$), suggesting the need to improve judgments in these cases. Next, the optimal RTO value is determined. To apply equation (10), we proceed by determining the estimated total impact (Fig. 4) and the average RTO value, which was averaged within the organization's sector for that incident (Fig. 5).

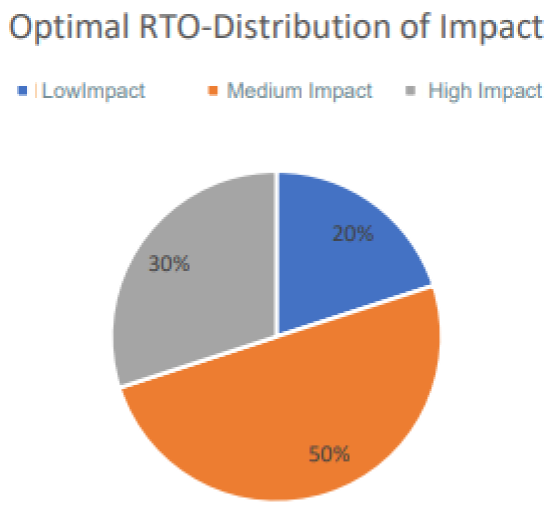

Figure 4: RTO Optimal-Distribution Impact

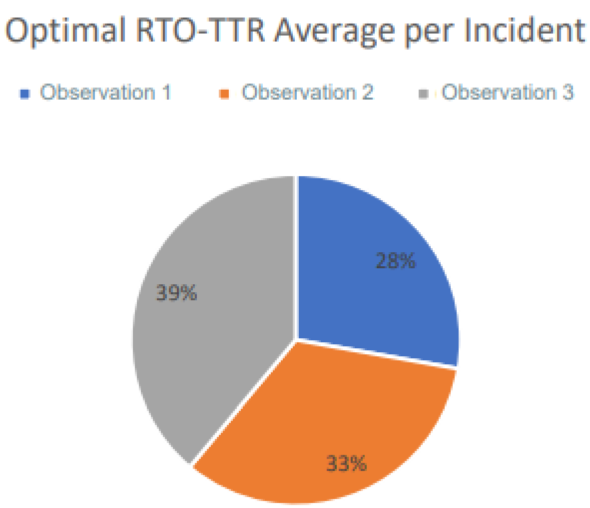

Figure 5: RTO Optimal-TTR Average per incident

Fig. 4 illustrates the distribution of the impact of incidents relative to the optimal RTO. As shown, medium impacts (50%) dominate the analysis, indicating that most incidents have intermediate severity. Low (20%) and high (30%) impacts are less frequent but still warrant attention, particularly those with high severity. Analyzing the average Time to Recovery (TTR) per incident, the data for the three observations indicate an average TTR ranging between 2.5 and 3.5 hours. This variation highlights that some projects may require more efficient recovery processes to meet the target RTO. After determining the acceptable RTO value, the company conducts a statistical test to verify whether the observed RTO aligns with the target RTO. A Student's t-test is performed, which, at a 5% significance level, supports the acceptance of the hypothesis (Fig. 6). Fig. 4 illustrates the distribution of the impact of accidents with respect to the optimal RTO. As can be seen, medium impact (50%) dominates the analysis, implying that most accidents have an intermediate severity.

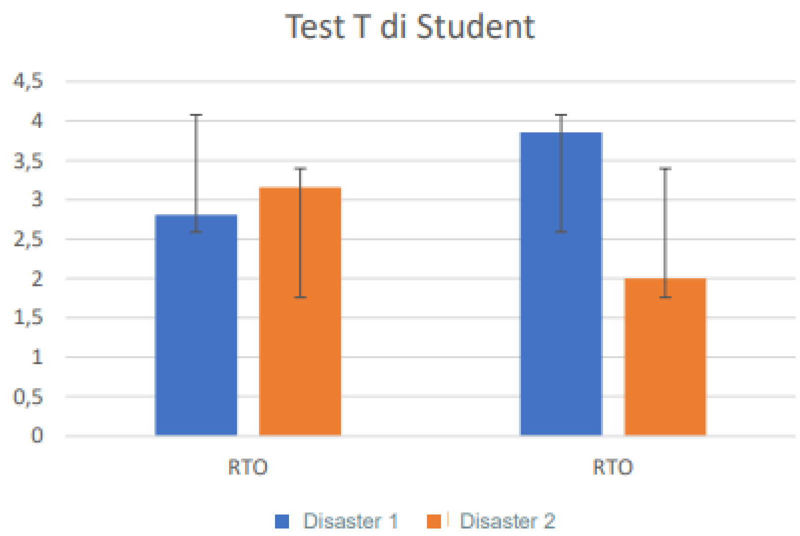

Figure 6: Student's t-test interpretation

The graph displays the RTO values for each incident. The blue bars represent the mean Target RTO values, while the orange bars represent the mean observed RTO values. Adding error bars to the graph, which indicate the variability of the data around the mean values, shows that the bars do not overlap. This suggests a potential statistical difference in the data. In other words, the variability in the data is unlikely to account for this difference purely by chance. This preliminary analysis suggests the existence of a statistically significant difference in the data. However, the absence of overlap alone does not always guarantee statistical significance, as it also depends on the sample size and the selected significance level. For this reason, the p-value associated with the performed t-test was also examined.

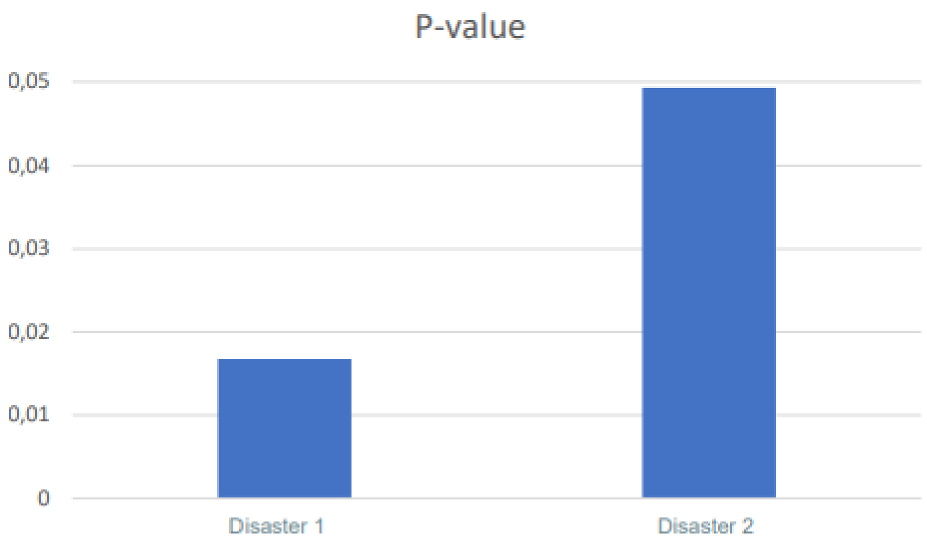

Figure 7: p-value trend on the t-Student test

This graph demonstrates that the likelihood of accepting the null hypothesis—namely, that the observed RTO aligns with the optimal RTO value—is strongly supported, with a 95% confidence interval in the case of Incident 1. However, for Incident 2, the p-value relative to the established threshold parameter prompts further consideration regarding the acceptability of the null hypothesis. Lastly, the financial impact associated with the determined RTOs is evaluated (Fig. 8).

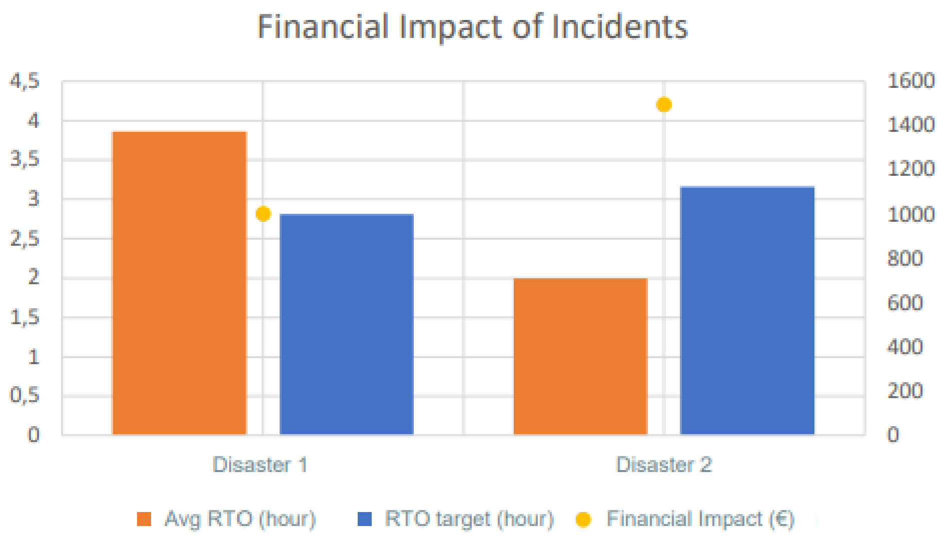

Figure 8: Financial Impact of Incidents

The graph illustrates the following for each incident: the blue bars represent the Target RTO values for each project, indicating the recovery time targets; the orange bars display the observed Average RTO values, showing how the actual recovery times compare to the targets. Finally, the yellow dots indicate the Financial Impact associated with each project, illustrating how economic costs increase with prolonged downtime. The figure demonstrates that, for Project 1, there is a high likelihood of resolving the failure within approximately 3 hours, consistent with the defined target. This is accompanied by an average financial impact of approximately €1,000. This suggests that the organization is well-aligned with its recovery objectives. Regarding the second project, the target RTO value of 3.16 hours was largely achieved by the organization, as the observations show an average RTO of 2 hours. This is a significant result for the organization, given that the financial impact of this failure, amounting to approximately €1,500, is substantially higher than the impact observed for the previous incident.

V. CONCLUSION

The Recovery Time Objective (RTO) is a critical indicator for operational continuity. Since the RTO value is tailored to the characteristics of a specific incident, it must be calculated using a highly targeted approach. This ensures the definition of an optimal recovery time that is both realistic and effective for each risk scenario, minimizing the risk of operational damage and enhancing disaster response capabilities. Introducing statistical analysis to monitor the achievement of RTO objectives is crucial. It allows verification of whether recovery times align with predefined targets while identifying deviations from established parameters. Such deviations could highlight critical areas requiring corrective action, thereby improving the effectiveness of Business Continuity processes. Moreover, integrating the economic dimension is essential for making informed decisions. If recovery time significantly impacts costs (e.g., halting production or harming the company's reputation), it is vital to understand how much an organization is willing to invest to reduce downtime. Corporate strategy must balance the cost of continuity measures with the potential financial impact of recovery time. The proposed model demonstrates the feasibility of determining an acceptable RTO tailored to each type of incident. Additionally, introducing statistical analysis enables the verification of whether the acceptable RTO aligns with predefined targets, identifying deviations that require adjustments to continuity processes. Finally, incorporating economic considerations helps guide corporate strategy based on the financial impact of recovery time, supporting targeted decisions in the realm of Business Continuity. Since this is an initial approach to such a strategy and considering that the proposed case study was designed solely to test the model's validity, the future research prospects in the context of Business Continuity and the Recovery Time Objective (RTO) are extensive and offer various avenues for exploration. In particular, a future research direction could focus on the use of AI-based predictive models to assess the economic impact of disruptions in greater detail and with higher accuracy. AI could be employed to simulate various economic scenarios in real time, analyzing the financial sustainability of a company under different recovery conditions and suggesting optimal strategic decisions for resource allocation. Another area of research could delve into change management and psychological resilience within organizations. How do individuals and teams adapt during crises? How can recovery processes be supported by human capital and its adaptive capacities? This could include studies on how leadership practices and communication influence recovery success. Finally, an intriguing perspective concerns the relationship between Business Continuity and sustainability. Companies are increasingly required to reduce the environmental impact of their operations and ensure long-term sustainability. Exploring how continuity practices can align with environmental and social goals will be an emerging theme, particularly concerning green regulations and certifications

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