A STOCHASTIC MODEL TO QUANTIFY AND OPTIMIZE THE IMPACT OF OPERATIONAL RISKS ON CORPORATE SUSTAINABILITY USING MONTE CARLO SIMULATION

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Abstract: Operational risk has been widely studied, and international guidelines provide procedures for the correct management of operational risk; however, this has not been studied from a corporate sustainability point of view. Therefore, this work seeks to find a way to model and optimize the impact of operational risks on corporate sustainability. The methodology used is based on the assignment of two distribution functions for the creation of a probabilistic model that allows quantifying the probability of occurrence (frequency) and the expected monetary impact (severity) on the sustainability variables (environmental, social, and economic). The result is a statistical convolution through Monte Carlo simulation, which makes it possible to quantify aggregate losses to finally make an optimization process of the variables and estimate the financial impact. Therefore, this study extends the literature on risk quantification, proposing a stochastic model that quantifies and optimizes the operational risks that are related to corporate sustainability. The proposed model offers a practical way to quantify operational risks related to corporate sustainability while also being flexible, as it does not require historical information and can be used with data collected from the company based on the proposed probability distributions. Finally, the proposed model has three limitations: the distribution functions, use of Solver (Excel), and exclusion of some risk management strategies, which future research can consider.

Key words: Operational Risk, Sustainability, Monte Carlo Simulation, Optimization

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Introduction

Operational risks generate unexpected losses resulting from the performance of the company's operations. Therefore, it is necessary to develop models to predict losses

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and associated operational risks to reduce the associated risks (Cornalba and Giudici, 2004). Risk management used by organizations includes methods and processes for identifying, managing, and predicting uncertainty (Makarova, 2021). In recent years, there has been a paradigm shift in risk management towards a holistic view of risk management (Zhao et al., 2015).
This study focuses on measuring the operational risks that affect corporate sustainability from a holistic point of view. Therefore, information is identified on risk modeling and quantification techniques, revealing that there are various methods available, but when searching for operational risk models that quantify the impact on corporate sustainability, it is evident that no specific model measures the impact of risk on sustainability. In the literature, there are approximations for quantifying environmental, social, and economic impacts. However, the quantification and optimization of risk remain open-ended (Griffy-Brown et al., 2019).
This research aims to develop an operational risk model to extend the literature on risk quantification. So, this study quantified the causes and consequences of risks in a simulated setting. For this, a standard distribution function for frequency and severity was selected because there are many companies for which no historical information is available to identify appropriate statistical models. Contrary to the selection of distribution functions, sufficient data must be available to identify suitable statistical models. This offers a practical way to quantify operational risks related to corporate sustainability while also being flexible, as it does not require historical information.
Given these distribution functions, operational risk losses may be measured due to the convolution between frequency and severity (Cornalba and Giudici, 2004). This is known as the possible inherent risk (Andersen and Häger, 2010) to the company owing to its operational exposure. Subsequently, this research based on the model seeks to reduce the negative impact on companies and improve business performance and profitability by optimizing business management efficiency (Zhang, 2020). Hence, an optimization process is carried out to quantify the importance of cost optimization (Rakhaev, 2020) through the analysis of the budget allocation to undertake risk management so that companies can find the optimal parameters (Zhu et al., 2022). To develop the research, the next section explains the literary background, followed by the methodology used; the researchers present the results, the critical discussion, and finally, the conclusions and the references.

Literature Review

Monte Carlo analysis has been used to estimate risks (Jaco et al., 2021), because uncertainty analysis provides information about the distributions that explain the results (Parolin et al., 2021). This type of analysis involves statistics, probability, and the assignment of theoretical distribution functions (Chang et al., 2018).
In contrast, stochastic analytics studies show that this type of analysis helps reduce uncertainty and increases the reliability of the risk-associated data (Kerim and Zeynep, 2021). In the case of losses due to operational risk, random variables are

assigned to characterize a risk event, where (Peña et al., 2018) frequency defines the number of times a risk event is repeated in each period, and severity shows the number of losses expressed in a currency over a period. Generally, frequency is modeled using discrete distributions, whereas severity is modeled using continuous distributions. However, there are many companies for which no historical information is vailable to carry out this type of modeling (Cruz, 2006). Therefore, this research oversees selecting a standard distribution function for both frequency and severity, where any company can use its information to generate the input parameters and model from standard distributions. This is supported by the fact that several authors have shown that a key concept for modeling is the adequacy of the information available, thus, reducing uncertainty, ambiguity, and complexity (Pich et al., 2002). In addition, some of the methods are insufficient to model the variables and behavior of the processes, which represents a lack of crucial information to make accurate forecasts.
Due to the above, the research question arises: How to model the operational risks that have an impact on corporate sustainability? For which the following research methodology is designed:

Research Methodology

This study commences with a comprehensive literature review, utilizing Scopus samples and employing data export as the data collection technique to gather information encompassing titles, abstracts, and keywords. The primary objective is to scrutinize existing models pertaining to operational risk. Subsequently, the study proposes an experimental design that allocates experimental units to various treatment levels. This is followed by a thorough statistical analysis of the model (Kirk, 2019). Thus, it carries out a simulation process that consists of repeating or duplicating the characteristics and behaviors of a real system. In (Channell, 1989), in most situations, it is based on an approximate model and learns about this model with approximate solutions based on theories and experimental verifications.
To develop the model, the standard steps for quantitative risk assessment proposed by (Chen et al., 2020) were taken as a reference.
Then, the optimization formulation provides the flexibility to effectively incorporate the risk-return trade-off (Zhu et al., 2022) by providing a mechanism to integrate risk management activities and optimize performance. In this investigation, an optimization problem is formulated to reduce losses and costs (Cruz, 2009) using budget allocation analysis to perform risk management and maximize business value following risk and uncertainty quantification (Michalski, 2009). In this research, optimization entails the reduction of operational risk exposure for companies, thus influencing corporate sustainability by minimizing the expenses associated with risk management. This is achieved through the optimization of budget allocation designated by companies for risk control.
Once the risk quantification and its optimization are formulated, scenarios are created to verify the mathematical validity of the model through simulation with seed

values (Gkogka et al., 2013). These are done with stress analysis on the limits of the distribution results to confirm that the simulation outcomes give consistent values. Based on these results, the researchers have obtained a stochastic model based on the standard steps for quantitative risk assessment, which consist of performing probabilistic analysis, consequence analysis, risk calculation, and risk decision-making (Chen et al., 2020) presented below.

Research Results

This section presents the standard steps for the quantitative evaluation of risks proposed in the methodology, and then the development of the model and the step-by-step are presented.

Probabilistic Analysis (Distribution Function Selected for Frequency)

The operational risk measurement frequency is modeled using discrete distributions (Peña et al., 2018), where the most popular discrete probability distributions are Bernoulli, binomial, geometric, hypergeometric, multinomial, negative binomial, Poisson, and discrete uniform. However, for modeling the frequency in operational risk measurement, distributions such as binomial (Klenke and Mattner, 2010), negative binomial (Elbatal et al., 2010), and Poisson distributions (Jayasree and Swamy, 2006) are taken. In the measurement models, the operational risk events highlighted the Poisson distribution (Hussain, 2020), where the Poisson distribution follows a distribution with parameter λ defined for a time interval (Beltrán-Beltrán and O'Reilly, 2019), as shown in Figure 1.

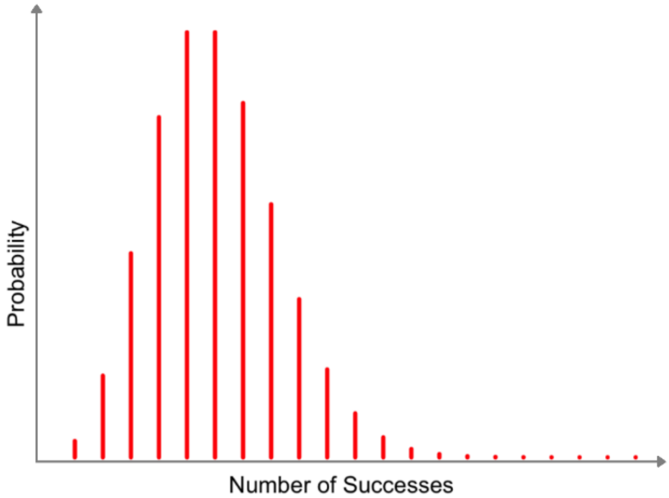

Figure 1: The Poisson distribution adapted by authors

Density function of the Poisson distribution, where X represents the number of outcomes occurring in each time interval t, and λ is the average of the results per unit of time, is (Jayasree and Swamy, 2006) shown in Equation 1:

$$p(X = x) = \frac{e^{-\lambda t}(\lambda t)^x}{x!} \quad x = 0, 1, 2 \ldots, \lambda > 0$$

Equation 1. Density function of the Poisson distribution

Consequences Analysis (Distribution Function for Severity or Monetary Losses)

In this investigation, different continuous distributions are analysed to define the severity distribution function, such as the normal, lognormal, uniform, triangular, and program evaluation review technique (PERT) distribution functions, and subsequently selecting the PERT distribution function.

The selection of the distribution model is supported by other authors who have previously conducted comparisons between these distributions (i.e., normal, lognormal, triangular, and PERT) and have shown in the results of their investigations that there is no significant difference in the output distributions when these are used as input distributions with the same mean and variance values (Visser, 2016). In addition, some authors have previously used the PERT distribution function to simulate and analyze risks (Pan and Xin, 2013) through the three-point (Sackey and Kim, 2019) discovery in the literature that this distribution is widely used due to its flexibility to adapt to situations in which the absence of specific data does not prevent having a global idea of the statistical behavior (Forcael et al., 2018). The existing literature on the PERT revealed that the PERT distribution is a traditional method for modeling uncertainties (Liu et al., 2021). It uses a three-point estimation method, i.e., the optimistic, pessimistic, and most likely points (Chang et al., 2019). Figure 2 below shows the points of a PERT distribution function.

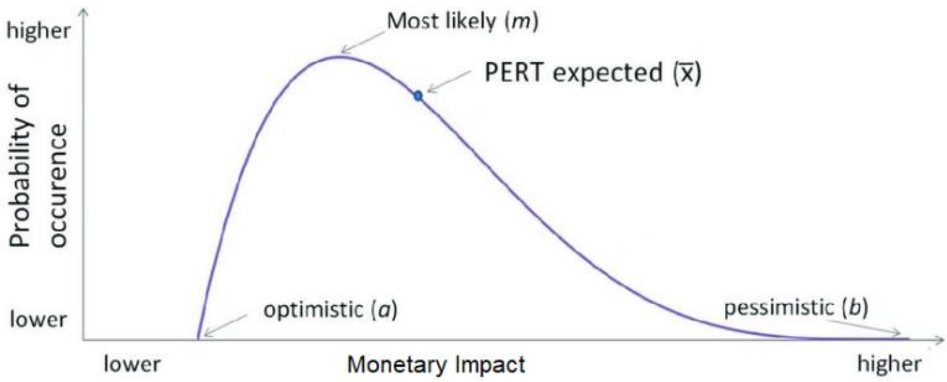

Figure 2: The PERT distribution (Hajdu and Bokor, 2016).

This can be explained by the mean expressed in Equation 2 and the variance in Equation 3 below:

$$X = \frac{a + 4m + b}{6}$$

Equation 2. Mean of the PERT distribution

Variance, σ_x^2 is defined in Equation 3:

$$\sigma_x^2 = \left(\frac{b - a}{6}\right)^2$$

Equation 3. Variance of the PERT distribution

Risk Calculation and Risk-Decision Making

The literature has been investigating how to identify, analyze, predict, evaluate, and manage different types of risk (Chen and Zhao, 2022) without much success. Therefore, this paper aims to fill this gap by providing steps for managing operational risk related to corporate sustainability. After determining the variables, the design of the simulation system is developed, in which the detailed model design is described. According to (Zhang and Wang, 2021), the simulation system must have information for the estimation of the distribution for probability, the estimation of the distribution for impact, and the method for calculating the aggregate losses. Hence, each of the steps to be followed is explained below.

Step 1: Risk evaluation – Identification: Identify the operational risks that generate environmental, social, and economic impacts, defining causes, risks, and Consequences.

Step 2: Assign quantitative information to quantify the frequency: Use the Poisson distribution: the probability that the event can materialize in a year must be inputted. This simulates whether risk materializes and how many times it materializes per year.

Step 3: Assign quantitative information to quantify the severity: Use the PERT distribution for the consequences, assigning the minimum, most likely and maximum impact.

Step 4: Quantify the sampling impact by a convolution: To quantify the sampling impact for each sustainability pillar, the statistical convolution of random variables was quantified for each risk (Bertsch et al., 2014). A convolution is an operator that transforms two functions, pi and xi, into a third function, where the convolution of pi and xi is denoted by pixi and is defined as the integral of the product of both functions after shifting one of them by a distance, t, (Razminia and Razminia, 2022) as shown in Equation 4.

$$(P_i X_i) = \int_{-\infty}^{+\infty} P_i(n) X_i(t-n) dn$$

Equation 4. Convolution process is defined as the integral.

The effect of convolution in practice is to create probability distribution functions (PDF; Mitchell et al., 2005). So, to quantify the expected losses for each pillar of sustainability, inherent risk must be calculated, which is the sum of the product of each risk impact with its probability (Capone and Narbaev, 2022) as is shown in Equation 5, so the total losses are the sum of the sample impact by group:

$$\sum (impact_i * probability_i)$$

Equation 5. The expected losses

The previous formula is applied for each of the sustainability pillars: Equation 6 for environmental effects (Theta θ), Equation 7 for social effects (Phi φ), and Equation 8 for economic effects (Epsilon ε).

$$\theta(t) = \sum_{i=1}^{n} p_{ai} x_{a_i}$$

Equation 6. The expected losses due to environmental effects

$$\varphi\ (t) = \sum_{i=1}^{n_t} p_{si} x_{si}$$

Equation 7. The expected losses due to social effects

$$\varepsilon\ (t) = \sum_{i=1}^{n_t} p_{ei} x_{ei}$$

Equation 8. The expected losses due to economic effects

Step 5: Calculate the total expected losses and analyze losses: Upon obtaining the calculations for losses associated with each sustainability pillar, it becomes necessary to determine the total expected losses at a specific time, denoted as "t." This total expected loss is determined by adding together the losses attributed to environmental, social, and economic impacts. Equation 9 provides the formula for calculating the Total Expected Losses at time "t."

$$Total\ expected\ losses(t) = \sum_{i=1}^{n} \theta\ (t) + \varphi\ (t) + \varepsilon\ \ (t)$$

Equation 9. The total expected losses

If the sum of the total losses (Equation 9) exceeds the value of equity, a consequence of the temporary effect (Lozano and von Haartman, 2018) is incurred, and the company can enter bankruptcy. Then, the total expected losses must be included as an output in the simulation and analysis and run the Monte Carlo simulation. Descriptive statistics were analyzed to quantify the impact of risks on corporate sustainability.

Risk control management was conducted to optimise the model after considering the potential losses that the company may incur due to the materialization of operational risks. The next step demonstrates how risk control is used to implement model optimization.

Step 6: Risk control: There are different ways of reducing exposure through the use of risk controls (Zhang, 2020). Four strategies are available for dealing with threats (Hosny et al., 2018): avoidance, acceptance, transference, and mitigation (Kouloukoui et al., 2019). Avoidance is eliminating a threat by eliminating its cause. Thus, the company must decide on the strategy to select the elements that make up each control.

Step 7: Risk control information: Once the company decides on the strategy, it must select the elements that make up the selected control.

The mitigation strategy helps to reduce the probability of risk entry and the expected loss (Hoang and Ruckes, 2017), the transfer strategy takes actions that transform the consequences of risk to a third party, which also means transferring the responsibility of risk (Keshk et al., 2018). When the company decides to assign controls, they are associated with a cost (Finger et al., 2018). These risk management costs must demonstrate the economic benefit of risk reduction (Shreve and Kelman, 2014). Therefore, the company must have a budget, which is analyzed in the next step.

Step 8: Budget: Risk reduction has been recognized in the literature for its role in mitigating negative environmental, social, and economic impacts (Shreve and Kelman, 2014), where corporate sustainability and the capability to estimate and reduce an organization's business risks are undoubtedly becoming indispensable plans of companies (Hui and Fatt, 2007).

Therefore, if a company wants to manage risk to minimize its impact, it has a cost that is generally associated with budget restrictions (Mohsni and Otchere, 2014) that are assigned to the financial department (Cousin et al., 2016), management (Laínez et al., 2009), and even the government (Le et al., 2021). Therefore, the company must request a budget allocation to reach an optimal coverage decision. Therefore, in the next step, budget allocation and losses from operational risks related to sustainability must be optimized to ensure effective planning, which protects and creates organizational value (Wang et al., 2021) associated with risk management.

Step 9: Optimize: Mathematical optimization is the process of formulating and solving a constrained optimization problem (Snyman and Wilke, 2018). This research seeks a new approach to optimize not only the losses due to risk generated by operational risks in companies related to corporate sustainability but also the optimal management of the assignment of controls to manage risks.
For this purpose, this investigation seeks a cost function that aims to minimize risk exposure and the costs associated with the management of each risk Ci.
The function presented below explains the quantification of the cost, Ci, that the company has for each risk control, i defined in each process. The function presented in Equation 10 explains the quantification of the costs that a company has for every risk control defined in each process.
The company must optimize the allocation of risk control, which is expected to minimize the risks and costs generated by applying the controls. For this, there is a determined cost of control and a percentage of risk coverage, as defined in Steps 7 and 8; thus, the model indicates which controls should be used and how many times that control should be used. To formulate the objective and constraint functions (Snyman and Wilke, 2018), the structure of the optimization of the model is presented in Equation 10.

$$f(x) = Total\ Risk\ cost\ after\ apply\ controls$$

Where the model wants to Minimize $f(x)$ as $\frac{min}{x} f(x)$

$$f(x) = \sum_{i=1}^{n} C_i\, T_{ci} + Resid\ Risk * p_i$$

Equation 10. Total risk cost after applying controls

Where:
C_i= Cost of risk control
T_{ci} = Control assignment times
Residual risk = Remaining impact after using risk control
$Resid\ Risk$ = Inherent risk * (1-%Cov)
Inherent Risk = Total expected losses (t) = $\sum_{i=1}^{n(t)} \theta\ (t) + \varphi\ (t) + \varepsilon\ (t)$
% Cov = % of coverage
B_a = Budget allocation
Pi = Probability of residual risk occurring

Constraints or restrictions:

1. $\sum_{i=1}^{n} C_i * T_{ci} + Resid\ Risk * P_i \leq B_a$

2. $\frac{min}{x} f(x) < Inherent\ Risk$
it means that.
$\sum_{i=1}^{n} C_i T_{ci} + Resid\ Risk * P_i < \sum_{i=1}^{n(t)} \theta\ (t) + \varphi\ (t) + \varepsilon\ \ (t)$

3. $Resid\ Risk \geq 0$

The above model can be used to:
-Minimize the inherent risk by applying controls considering the percentage of coverage, which is known as residual risk.
-Optimally allocate the budget that will be used to control risk by analyzing the cost and time that the control is assigned.
-Determine the total cost of risk exposure; that is, analyze the costs of controls and the inherent risk for business decision-making.
Finally, budget allocation is done optimally to assign the controls that can be applied depending on the budget and manage the risks to reduce losses, applying risk management strategies to enhance shareholder value and company performance.
Step 10: Decision-making: An epistemic perspective acknowledges that decision-makers recognize uncertainty when projecting into the future (Luther et al., 2023). Therefore, it is necessary to make risk-aware decisions through the explicit quantification of risks (Zheng et al., 2019) to determine the risk profile of the company, and enable risk acceptance or mitigation decisions that support decision-making under uncertainty. Simulation-based optimization techniques can help risk managers improve the quality of their decisions (Oliveira et al., 2019). Hence, this study uses simulation to help make decisions based on effectively capturing and integrating quantitative and qualitative information.
The results of this model can provide answers as to why the literature seeks to prioritize budget management for mitigation efforts and, thus, prioritize the decision criteria. Using the findings from earlier results, the company can make informed choices about how to manage operational risks. This helps validate how these actions affect the overall sustainability of the company by providing clear and objective measurements to guide strategic decisions. Additionally, it helps optimize the company's financial resources by using techniques like optimization and simulation to enhance the decision-making process.

Discussion

In light of this theory, the model presented in this research is developed considering the standard steps for quantitative risk assessment proposed by Chen et al. (2020), which includes probabilistic analysis, consequence analysis, risk calculation, and risk decision-making. The model is based on the need to generate risk models that do not require historical information (Shojaeimehr and Rahmani, 2022), since companies have evidenced this need, according to authors such as Cruz (2006).

The method proposed in this research starts with the identification of risks that it follows, in line with the theory that lies in defining the causes (Yang et al., 2018), risks, and consequences to subsequently assign quantitative data of frequency and severity for each pillar of sustainability.
Previous studies identified that probability distributions can be used for risk measurement (Peña et al., 2018), so this research assigns a discrete distribution for frequency, taking Hussain (2020) as a point of reference, for which this research assigned a Poisson distribution, and a continuous distribution for severity following authors such as Pan and Xin (2013). A PERT distribution is selected, where a statistical convolution (Mitchell et al., 2005) is performed for the quantification of aggregate losses. Finally, an optimization process (Zhu et al., 2022) is performed to comprehensively analyze the company's risks and their management.
The literature review provided a basis for the creation of the model. However, the sustainability pillars were linked to this quantification, creating a new methodology that contributes to the literature by classifying the sustainability pillars and performing quantification, leading to results in terms of corporate sustainability. For this, the classification of corporate sustainability proposed by Lozano and von Haartman (2018) was taken as a reference. In this way, a contrast can be generated between the existing literature and the results found. Although the model is mainly based on existing risk theories and methods, this novel operational risk model presents a new relationship between operational risks and corporate sustainability.

Conclusion

When reviewing the literature on the modeling of operational risks that impact corporate sustainability, it became evident that there are models used in previous studies that allow quantifying operational risk primarily based on statistical models that approximate the expected losses of the companies. Although there are approximations of quantifications for some specific pillars of sustainability, such as losses due to environmental effects, social responsibility indicators or economic losses due to risk materialization, a model that allows estimating operational risks in light of corporate sustainability as a holistic analysis of the company was not found. The models developed by other researchers show that operational risk quantification usually employs the Monte Carlo simulation methods. This study also uses methods developed in previous literature, using this type of quantification as a reference.
However, the current models require historical information and are not fully linked to corporate sustainability. To identify the limitations of companies who want to quantify operational risks and do not have historical information available, this research proceeds to evaluate Monte Carlo simulation methods, which are the most used distributions in the literature for this type of modeling. According to authors who have been developing this type of analysis over time, frequency is normally modeled using discrete distribution functions, and severity is normally modeled using continuous distribution functions.

Based on the experience of these authors, and with the aim of benefiting the scientific community and companies that require quantification of operational risks, which are also related to corporate sustainability, this study proceeds with the selection of two distribution functions. The first one explains frequency based on a Poisson distribution, and the other explains severity through a PERT distribution, allowing the company to quantify the risk based on company parameters or expert opinions that allow approximating these values.

Therefore, the results of this study can be interpreted from the perspective of previous studies as an option to provide tools for companies that do not have historical information for risk modeling.

Finally, an optimization process is conducted to reduce the impact of risks on the company through risk control by optimizing the company's budget allocations. After developing the model and analyzing different scenarios for the results, the model has three limitations. First, by suggesting the Poisson and PERT distribution functions as standard distribution functions, the results can generate biases, be limited, and even be manipulated. Second, Solver (Excel) has problems with relative minima and maxima solutions. Third, the model considers only three of the four strategies proposed in the literature regarding risk management because the model makes budgetary allocations for reduction and transfer and suggests the acceptance of risks in some scenarios. However, avoidance was not considered, and hence, this strategy is not considered as a means of risk control in the methodology of this research. Future studies should investigate budget allocation analysis to find a way to use resources optimally. In addition to the findings of this study, it is possible to indicate whether budget allocation should be used to reduce frequency through mitigation strategies, reduce severity through transfer strategies, or combine both strategies to define the optimal risk management strategy.

In addition, this research emphasizes modeling; therefore, in future investigations, it is suggested to examine in detail the processes of identification and monitoring of risks that are a part of integrated risk management, as indicated in the literature.

Finally, the primary contribution of this study is that it is a practical model for companies to implement the quantification of operational risks and demonstrate their impact on corporate sustainability by modeling the frequency, severity, and calculation of aggregate losses through the 10 steps proposed.

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MODEL STOCHASTYCZNY KWALIFIKACJI I OPTYMALIZACJI WPŁYWU RYZYKA OPERACYJNEGO NA ZRÓWNOWAŻONY ROZWÓJ KORPORACYJNY Z WYKORZYSTANIEM SYMULACJI MONTE CARLO

Streszczenie: Ryzyko operacyjne zostało szeroko zbadane, a międzynarodowe wytyczne dostarczają procedur do prawidłowego zarządzania ryzykiem operacyjnym; jednakże nie badano tego z punktu widzenia zrównoważonego rozwoju przedsiębiorstwa. Dlatego też niniejsza praca ma na celu znalezienie sposobu modelowania i optymalizacji wpływu ryzyka operacyjnego na zrównoważony rozwój przedsiębiorstwa. Zastosowana metodologia opiera się na przypisaniu dwóch funkcji rozkładu w celu stworzenia modelu probabilistycznego, który pozwala kwantyfikować prawdopodobieństwo wystąpienia (częstotliwość) i oczekiwany monetarny wpływ (ciężkość) na zmienne zrównoważone (środowiskowe, społeczne i ekonomiczne). Rezultatem jest statystyczna konwolucja poprzez symulację Monte Carlo, który umożliwia ilościowe określenie zagregowanych strat, aby ostatecznie przeprowadzić proces optymalizacji zmiennych i oszacować wpływ finansowy. Dlatego też niniejsze badanie poszerza literaturę w obszarze kwantyfikacji ryzyka, proponując model stochastyczny, który kwantyfikuje i optymalizuje ryzyko operacyjne związane ze zrównoważonym rozwojem przedsiębiorstwa. Proponowany model oferuje praktyczny sposób ilościowego określenia ryzyk operacyjnych związanych ze zrównoważonym rozwojem przedsiębiorstwa, a jednocześnie jest elastyczny, ponieważ nie wymaga informacji historycznych i może być stosowany w połączeniu z danymi zebranymi z przedsiębiorstwa w oparciu o proponowane rozkłady prawdopodobieństwa. Wreszcie proponowany model ma trzy ograniczenia: funkcje rozkładu, użycie Solvera (Excel) i wykluczenie niektórych strategii zarządzania ryzykiem, które mogą zostać uwzględnione w przyszłych badaniach.

Słowa kluczowe: ryzyko operacyjne, zrównoważony rozwój, symulacja Monte Carlo, optymalizacja