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Risk Management and Assessment Hybrid Framework for Business Process Reengineering Projects: Application in Automotive Sector

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Abstract: This study introduces an integrated method for managing process risks in a Business Process Reengineering (BPR) project, using Robust Data Envelopment Analysis (RDEA) and machine learning (ML). The goal is to prioritize risks based on three standard factors of PFMEA: Severity, Occurrence, and Detection (S-O-D), and incorporating two additional factors (Breakdown Cost and Breakdown Duration) seen as undesirable outputs. The model also accounts for the effect of uncertainty on expert-estimated values by applying disturbance percentages in the linear PFMEA-RDEA model. A machine learning model is proposed to predict new values if partial or total modifications have been made to the processes. The approach was implemented in an automotive sector company, and the results showed the impact of uncertainty on values by comparing different approaches such as RPN, PFMEA-DEA, and PFMEA-RDEA. A new reduced risk categorization was achieved, who allowed for decision-makers to focus on necessary actions for reengineering.

Keywords: BPR; DEA; RDEA; machine learning; FMEA; PFMEA; risk prioritization; ANN

1. Introduction

Globalization has significantly transformed the business world, leading to rapid changes in operations and client demands. In this dynamic environment, commercial organizations face intense competition and significant challenges. The demands of the modern business environment highlight the necessity of adopting robust strategies to drive radical improvements in operational performance, efficiency and value creation. [1] Companies that fail to implement changes, often imposed by customers or the general environment, have a risk to lose their competitiveness and might even disappear from the market. [2] Business process management therefore serves as a systematic approach essential for accomplishing work and achieving set objectives [3].

Reorganizing and redesigning traditional business processes are key steps for manufacturing organizations aiming to improve operational efficiency, adapt to changing market demands, and maintain or boost their competitive advantage. Business Process Reengineering (BPR) is recognized as the best method in response to these needs. Its main goals are to cut costs, meet deadlines, and enhance the overall quality of manufacturing. If implemented correctly, it is the only method capable of delivering exceptional results. [4,5] Currently, BPR is the most popular approach for driving changes and has garnered considerable attention from academics and practitioners. [6–9] Numerous studies have revealed that implementing BPR is highly risky, with 80% of projects failing. [10,11] Other research shows that the success rate of BPR projects is only 30%. [7,12] Additionally, 70% of projects do not achieve the expected outcomes. [13] The challenge of defining success factors creates significant difficulties in developing frameworks and methodologies. Moreover, implementing a robust risk management strategy is crucial. [14]

Numerous methods exist for assessing risks, yet an effective evaluation technique must be customized and simple to reflect the specific activities, culture, processes, and other characteristics of an organization. Risk assessment involves a methodical approach to determining both quantitative and qualitative risks tied to hazardous processes, materials, activities, or events that could impact humans, materials, equipment, and the environment.[15] Among the various methods for risk assessment, FMEA (Failure Mode and Effects Analysis) is distinguished by its proactive approach to identifying potential issues, as opposed to reactive methods. FMEA entails the identification of possible problems and the assessment of their associated risks, followed by both formulation and implementation of corrective measures to minimize or eliminate these risks. Numerous studies employing FMEA utilize the conventional-RPN (Risk Priority Number) to identify and prioritize risks. [16–18] This score directs improvement initiatives towards risks possess a higher RPN, although potentially less severe, compared to other risks with a lower RPN. [19] Traditional FMEA incorporates just three metrics" SOD" (Severity, Occurrence, and Detection) as the key elements for calculating the RPN in risk assessments, which present a limit for the traditional RPN's effectiveness. Consequently, in employing FMEA for evaluating process risks, it is essential to include additional factors beyond the classic S-O-D metrics. To surmount the FMEA limitations, this study has integrated two extra variables: the cost and the duration of process breakdown. Nonetheless, based on the specific nature of the risk and the circumstances of its occurrence, these additional variables can fluctuate and introduce a level of uncertainty that can make prioritization unreliable and even impractical when fixed values are assigned to these variables.

DEA (Data Envelopment Analysis) is extensively utilized to evaluate the efficiency of Decision-Making Units (DMUs) across diverse sectors, aiming to boost organizational performance in various activity areas. [20] DEA has also been employed in evaluating organizational risks. [21] There has been considerable investigation into deterministic DEA methods to understand the connection between various risk facets and efficiency. DEA enhances the analysis and assessment of an organization's risk levels in activities by either extending or incorporating other methodologies, thereby assigning an appropriate prioritization score. [22] A notable drawback of DEA and linear programming models is their reliance on deterministic data that match nominal values, which overlooks the impact of data uncertainty on the model's effectiveness. [23] Consequently, robust optimization has emerged as an effective and reliable solution, presenting a strong alternative to stochastic programming and sensitivity analysis. [24]

When an organization uses DEA to assess risks and has already evaluated the risk level for a large number of Decision-Making Units (DMUs), reapplying DEA can lead to different results. [25] This happens because DEA uses data that evolve over time to perform the internal evaluation of DMUs. If it's necessary to recalculate only certain DMUs based on their new efficiency to represent their updated risk level, managers often reapply the DEA methodology in its entirety. This can change the efficiency scores of all DMUs, which can cause confusion in the process of decision-making, especially for risk treatment. Hence, this research introduces a ML (Machine Learning) approach to forecast new risk levels using efficiency scores. While earlier methods have merged DEA and ML to assess the efficiency of DMUs across different fields, their application in risk management remains unexplored. Risk treatment and monitoring are crucial components of risk management, involving the choice of suitable treatment strategies and the evaluation of their effectiveness, respectively. [26] To improve the risk management process, it is essential to devise effective methods and tools that can predict the potential outcomes of treatment strategies, leading to a more robust and comprehensive approach. AI (Artificial Intelligence) manifests itself like a useful methodology to monitor the impact of strategy variations on predicted variables. [27] For example, neural networks are a powerful tool in terms of risk monitoring. [28,29] There are two key advantages to using neural networks for estimation or prediction tasks. First, they are capable of processing large volumes of data for output estimation. Second, they can provide high accuracy in predictions. Moreover, the operational speed of neural networks is fast. [30]

To address all these issues, this study proposes an approach based on robust-DEA (RDEA) to obtain efficiency scores that prioritize risks, taking as inputs the critical factors of RPN from the FMEA process as well as the cost and duration of process downtime as undesirable outputs. This can provide reliable and realistic data that enable decision-makers to make informed decisions during the reengineering of the operational processes in question. The application of neural network models

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for forecasting in risk treatment and analyzing is another result of this study. The proposed approach has been applied to the assessment of process risks in an automotive spare parts company, and the results have been analyzed.

2. Literature Review

2.1. BPR

BPR has been a popular topic since it first came up in the early 1990s. Both researchers and professionals have explored its importance, methods, effects, and what makes it successful. [31]

BPR started in the early 1990s as an innovative method to rethink and revamp business processes for substantial improvements in areas like cost, quality, service, and speed. [32] Reengineering involves a thorough reengineering of business processes. [33] BPR is seen as a strategy where processes are reshaped to maximize an organization's effectiveness. [34] Another description of BPR is a management approach focused on completely revamping or replacing inefficient procedures to achieve significant results. [35] This method can be applied to one or several processes. According to Bhaskar, BPR is customized for each organization, so they use it in their own way to meet their specific goals. This approach works for businesses of all sizes, whether they are in manufacturing or services.[36]

BPR is a complete overhaul of a business, changing everything from processes and technologies to organizational structures, values and management systems. The aim is to greatly improve performance throughout the company. BPR needs to work together with other parts of the organization, use advanced technology, and incorporate different methods. It doesn't work well on its own. IT plays a key role in BPR by providing the tools needed for major improvements in how the organization functions, although its role can sometimes be misunderstood. [37,38]

To complete Successfully an implementation projects is a commendable feat for any team. Nonetheless, business process re-engineering projects frequently experience varying degrees of success. This inconsistency often stems from the application of best practices or standards from other industries without adequately considering the specific needs of the targeted industry. Notably, around 70% of these projects fail, due to the lack of an appropriate framework or methodology. [9]

Many factors affect the outcome of a project. These factors are important for predicting whether a project will succeed or fail. BPR projects come with their own risks. Whether BPR is successful depends on several key factors. [39].

By reviewing research, we have identified eleven main factors that determine the success of BPR projects and have pinpointed the major reasons why BPR projects fail.[40]

Table 1. T Success and Failure Factors.

Category	Factor	Success	Failure
Strategic	Focus to change	Readiness for change, courage and willpower	Lack of readiness and resistance to change
Driver	methodology and framework	selecting the best methodology and framework for the project	Lack of suitable and effective BPR framework and methodology
Enabler	working environment	Collaborative and work towards shared objectives and targets	Lack of collaborative working
strategic	Top management	Highly engaged, supportive, and committed	Lack of top management commitment
driver	BPR	Aligned strategies	Lack of reliable advanced

	strategies, IT capabilities (IT integration, IT infrastructure and redesign, etc.)		technology (IT)
enabler	Data	Data-driven change based on facts and figures	Not having sufficient data
enabler	Culture	Flat and less bureaucratic Structure	Poor leadership style
enabler	communication	effective communication, motivation	Lack of communication with all stakeholders
strategic	financial support	Adequate financial support	inadequate financial support
driver	Business needs analysis	Customer focus	Inadequate business case: unclear, unreasonable, unrealistic scope, and unjustifiable expectations from the BPR project
enabler	BPR team	effective and skilled BPR team Training, education, fair reward system Provided to all levels	Lack of training and education and fair reward

Although numerous factors influence the success of BPR projects, the human element is the most crucial. [41] Leveraging data and analytics to guide decision-making throughout the project can significantly impact its success. By understanding the variables that contribute to success or failure, and using data science and machine learning techniques, it becomes possible to predict the outcomes of a BPR project.

The re-engineering process is structured into stages, where the output from one stage serves as the input for the next. Before any implementation can begin, both the diagnostic and transformation steps must be completed allowing little room for flexibility. Numerous frameworks and strategies have been devised for carrying out BPR, with a common concern among practitioners being the choice of methodology or model to follow. It has been observed that many companies engaging in BPR tend to adopt conventional methodologies that use linear lifecycle models, influenced by traditional practices in engineering and software development. These approaches have faced criticism for their inconsistency and the variability of their stages. [42]

A comprehensive six-phase framework BPR was introduced.[43] The first phase requires top management to acknowledge their goals and motivations while committing fully to the initiative. In the second phase, management must establish a clear vision and set objectives to guide the company's activities. The third phase involves benchmarking to assess current processes and identify critical issues, establishing a baseline for the BPR project. The fourth phase entails conducting a pilot study to determine necessary resources and the extent of changes required. The fifth phase, implementation, is vital and necessitates support from middle managers and top management to lead, adjust reward systems, realign structures, educate employees, and implement IT for successful integration. Effective and ongoing communication throughout the organization is crucial to mitigate resistance. The final phase focuses on monitoring and evaluating the project, tracking progress, and identifying areas for adjustment.

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Other researchers have explored the development of frameworks to aid in selecting appropriate BPR modeling methods in response to heightened competition and a dynamic business environment. [44] Successful BPR planning requires comprehensive information and the right tools. BPM (Business Process Modeling) is highlighted as a technique for describing and analyzing business processes, with various methods and software available to assist practitioners and researchers in designing BPM.

BPR is a distinctive, one-time event and should be, like any critical project, managed, as it is essential for the future of an organization. It involves phases of analysis, design, and implementation, as depicted in the flow diagram in Figure 1. [45]

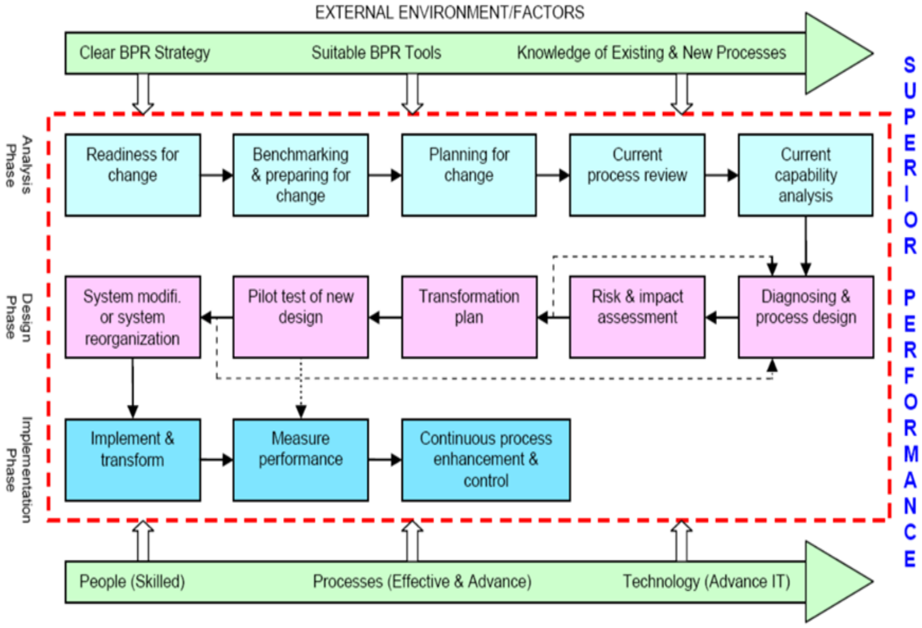

Figure 1. Proposed Framework for study.

The goal of this BPR framework and methodology is to assist organizations in their efforts. The stages of the model are detailed below:

In the phase of analysis, it is crucial to prepare for change by thoroughly understanding market and the requirements of customers. This step involves a detailed examination of current internal processes to determine their effectiveness in achieving competitive performance levels. Benchmarking against industry best practices is often included in this phase. Early in the process, decisions are made regarding which processes are most suitable for reengineering and which areas require immediate focus. It's noted that one of the most frequently suggested research areas for addressing the challenges of implementing BPR projects is the application of risk management and its techniques before, during, and after the project phases. [45]

2.2. Risk Management and Methodologies

Risk is present in almost every aspect of life. People try to reduce it, sometimes intentionally and sometimes because they have to, although completely getting rid of it is not possible. In the industrial world, the pursuit of significant investment returns has led to the development of many analysis methods.

To begin discussing risk and how it's managed, it's important to first understand what risk means. The term "risk" doesn’t have a single, fixed definition; its meaning varies across different fields like business, social contexts, economics, safety, investment, military, and politics. [46] In project management, risk is usually defined as the chance that something might happen that could either help (as an opportunity) or hurt (as a threat) the goals of a project. However, for those working in the field, managing risk mainly involves finding and reducing potential dangers. In the context of business process reengineering, risk follows the ISO 31000 standard definition: "the effect of

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uncertainty on objectives." [47] This effect refers to any variation from what was expected, whether good or bad. These objectives can be diverse, covering financial, time-related, technical, commercial, environmental aspects, and more, and can apply to different levels of operation such as strategic, organizational, product, or process levels.

In the context of enterprise operations, risk management typically entails four key activities: (i) risk identification, which determines the events that could adversely affect operational goals; (ii) risk assessment, an ongoing process that encompasses risk analysis and risk evaluation; (iii) risk treatment, the response to identified risks; and (iv) risk monitoring to oversee risk dynamics over time [26,48,49]. The risk management process advances to risk evaluation, where the magnitude and priority of each risk are determined based on benchmarking criteria set within the defined context [49]. The third stage, risk treatment, involves devising, choosing, and executing a plan of action. This pivotal phase necessitates the identification of suitable strategies to address the risks, particularly those deemed unacceptable after evaluation [50]. Finally, risk monitoring involves the ongoing oversight and reassessment of risk sources, as well as the effectiveness of risk treatment strategies. This step is critical because risk is dynamic, not static, necessitating periodic adjustments to management approaches as circumstances change [26].

Risk management frameworks usually integrate both quantitative and qualitative methods for identifying and assessing risks. These two approaches can sometimes produce conflicting recommendations in practice. [*52*] When ample data is available quantitative methods for assessments are favored, but such comprehensive data is often lacking. In these instances, while qualitative methods alone may not be ideal, developing a combined model to enhance qualitative risk management becomes essential. Techniques like Multiple Criteria Decision-Making have been employed in various situations involving risk and uncertainty, supporting the structured approach of risk management. [52,53].

2.3. FMEA

In recent years, several risk assessment methods have been developed, including FMEA. Originally introduced in the aerospace industry, FMEA focuses on identifying potential failures and their consequences to prevent defects, enhance safety, and boost customer satisfaction [54,55]. This method has gained widespread acceptance across various industries due to its utility for designers [55,57]. FMEA is a qualitative technique used in risk management and decision-making [58]. It prioritizes potential failures by assigning a RPN to each one [59]. The RPN is instrumental in improving production or services by managing, reducing, or eliminating failures. A higher RPN indicates a more urgent need for corrective or preventive measures [60]. The RPN is derived by multiplying three factors (S*O*D) denotes the frequency of a potential failure, "S" reflects the severity of its impact, and "D" gauges the likelihood of detecting the failure before it leads to further problems [61].

To prioritize risks in FMEA, a weight-restricted DEA method is used in a pressurized water reactor power plant. [62] other Studies combined a fuzzy belief TOPSIS approach with FMEA to enhance risk assessment in steel production. [63] other authors introduced a hybrid method that combines Grey Relational Analysis and interval DEA, and applicate it to process failure analysis for assessing and prioritizing risks in auto parts manufacturing processes. [64] Another approach by involves a new hybrid model using FMEA, TOPSIS, AHP and GRA for risk assessment in the production of automotive dust caps. [65] Razi and Hoseini conducted a study on clustering and classification in a production process and introduced a new method of FMEA by grouping failure modes using a KOHNEN neural network and SBM-DEA model to assessed them within their classes.[66]

In 2017, a study utilized a combination of TOPSIS and FMEA for risk analysis [67]. In place of the RPN, an ELECTRE TRI-based method was used to categorize failure modes in dairy manufacturing, considering the importance and uncertainty of risk factors [68]. A novel approach introduced in 2018 combined FMEA, extended MULTIMOORA, And AHP within a fuzzy environment to assess risks in the steel industry [69]. Another hybrid method merged Fault Tree

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Analysis (FTA) with FMEA, applied recursively in a metal printing additive manufacturing system [70]. Additionally, a strategy integrating FMEA with RDEA aimed at managing Health, Safety, and Environment (HSE) risks by targeting undesirable outputs [71]. Further studies highlighted productivity improvements in automotive manufacturing through the combined use of GRA and FMEA, while another methodology incorporated QFD, VSM, plant layout, and fuzzy FMEA to select lean tools in manufacturing organizations [72,73].

2.4. PFMEA

FMEA is a prevalent technique used to detect and mitigate defects and failures in systems by evaluating their impact on performance and implementing measures to reduce their likelihood and consequences. There are four primary types of FMEA: System FMEA, Design FMEA, Process FMEA (PFMEA), and Machinery FMEA. PFMEA specifically targets potential failure factors in production or assembly processes, aiming to decrease product failure rates early in the product lifecycle by addressing defects. In this method, the most critical failures are identified based on team member insights, resulting in a prioritized list of potential issues. Corrective and preventive actions are then devised and executed either prior to or during the process. Consequently, PFMEA is regarded as a dynamic document that must be continuously updated with recent changes and actions, including those implemented post-production and any new RPNs [74].

As mentioned earlier, the RPN is determined by multiplying the factors of “ SOD” as part of the PFMEA process. Each factor is rated on a scale from 1 to 10, with 1 representing the lowest risk and 10 the highest. For severity, a higher score indicates a "very dangerous" failure. For occurrence, it signifies the failure is "almost certain to happen," and for detection, it means the failure is "unlikely to be recognized" [75].

2.5. DEA

Research has highlighted several issues with the RPN used in the FMEA model [61]. The calculation method for RPN can lead to misleading statistics, and it fails to consider the interconnections between failure modes, especially in complex systems with numerous components [76,77].

While FMEA is a valuable risk assessment tool, it does not consider the relative importance of the “SOD” factors. To address this, many Multi-Criteria Decision-Making (MCDM) techniques have been used to evaluate failure modes and enhance FMEA outcomes, DEA. DEA evaluates the relative performance of different Decision-Making Units (DMUs). In this context, potential risks or failure modes in FMEA are treated as DMUs, with the S-O-D ratings from FMEA serving as inputs for the DEA. This integration forms a cohesive model combining FMEA and DEA [78].

In FMEA, risk factor weights are often assigned directly or confirmed through expert judgment. MCDM methods such as AHP and ANP are established techniques for this purpose [79]. DEA, however, offers an alternative method for assigning weights, enhancing FMEA by improving the assessment capabilities and providing precise information on factors like Severity, Occurrence, and Detection. Unlike other methods, DEA does not rely on subjective judgments about the relative importance of risk factor weights. Instead, it determines weights based on the interrelationships within the process [59]. The efficiency of a DMU is measured by comparing its performance to the best-performing unit, calculated as the ratio of the weighted sum of outputs to the weighted sum of inputs [80]. Additionally, DEA assesses the importance of risk factors through their weights and ranks failure modes by considering both the direct effects of individual failure indices and their impact relative to the efficiency scores of other DMUs. This makes DEA effective for adjusting the weights of risk factors by accounting for both indirect and direct relationships among failure modes [81]. The core principle of DEA is to optimize weights for each DMU to maximize the output-to-input ratio while ensuring the ratios of all DMUs remain close to one.

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2.6. Machine Learning in Risk Management

ML can be applied across various fields such as approximation, statistics, algorithm *complexity, analysis, and probability. Recent progress in deep learning, a subset of ML,* has produced outstanding results. ML algorithms simulate human learning behaviors to gain new knowledge and continuously improve prediction accuracy [25] .

ML, as a part of AI, leverages the rapid expansion of data. It excels in predictive and classification analytics, essential for making informed decisions based on data [81]. ML is increasingly influential in business, with numerous applications already in place and many more in development. [82]

The core function of ML is to use algorithms to analyze and learn from data, allowing these algorithms to make predictions on new data, thus aiding decision-making for various scenarios. ML encompasses unsupervised, semi-supervised, supervised, and intensive learning methods. Supervised learning, one of the most common approaches, trains neural networks on known data patterns for tasks such as classification and regression [25].

In predictive tasks, ML algorithms utilize historical data to forecast future events, improving their accuracy as they process more data. [83] This predictive accuracy is vital for effective performance.

In the business sector, ML has been particularly useful in risk management, such as assessing and predicting risk probabilities. For instance, ML has significantly impacted the financial sector, managing risks like credit, liquidity, operational, and market risks. Studies have demonstrated its application in banking risk management [84].

Additionally, ML has been employed in risk management systems to enhance investment portfolio performance by predicting potential losses. [8] ML's capabilities also extend to industrial risk assessment, where, for example, deep neural networks have been used to evaluate risks in scenarios such as oil and gas drilling operations [86].

Moreover, ML's predictive capabilities support evidence-based decision-making in the construction industry, enabling the development of proactive strategies based on dynamic risk factors. This facilitates more effective project risk management [87].

3. Proposed Approach

3.1. RDEA

DEA techniques for handling uncertain data were first introduced in 1978 twith aiming to assess the relative efficiency of distribution companies [88]. This non-parametric method creates a piecewise linear efficiency frontier, derived from the most efficient companies, to evaluate the relative efficiency of other firms. DEA is widely used in the electricity sector due to its straightforward application and ease of interpretation.

Within this context, two modeling options are available: constant returns to scale (CRS) and variable returns to scale (VRS). The CRS model assumes that companies can scale their operations proportionally to achieve the optimal firm size. In contrast, the VRS model offers greater flexibility by comparing the productivity of companies with others of similar operational scale. In the conventional DEA, a group of DMUs is established, using inputs $X_1, X_2, \ldots, X_m$ to produce outputs $Y_1, Y_2, \ldots, Y_s$ where m and s represent, , respectively, the number of inputs and outputs. For a DMU j, x_{ij} represents the ith input used, and y_{rj} represents the rth output produced:

$$\boldsymbol{\theta} = \frac{\sum_{r=1}^{s} \mu_r y_r}{\sum_{i=1}^{m} v_i x_i} \qquad (1)$$

In this model, μ_r and v_i represent the weights assigned to outputs and inputs, respectively. The multiplier formulation for an input-oriented approach that assumes constant returns to scale (CRS) is depicted in model (2):

$$\boldsymbol{max\,\theta} = \sum_{r=1}^{s} \boldsymbol{\mu_r y_{r0}}$$

$$\text{s.t. } \sum_{r=1}^{s} \boldsymbol{\mu_r y_{rj}} - \sum_{i=1}^{m} \boldsymbol{v_i x_{ij}} \le \boldsymbol{0} \qquad (2)$$

$$\sum_{i=1}^{m} \nu_i x_{i0} = 1$$
$$\mu_r, \nu_i \geq 0$$

As previously noted, DEA results and rankings are unreliable when data are uncertain. In real-world scenarios, it is often difficult to obtain precise data for inputs and outputs in DEA applications. Traditional operational research modeling methods that address uncertainty typically rely on a complete description in terms of probabilities. However, uncertainty is often completely overlooked in many models. Recently, the emergence of robust optimization has offered another alternative to sensitivity analysis and linear programming. [89,90] The initial approach was introduced in 1973, who proposed a model that handles uncertainty on a column-by-column basis. This model tended to be overly conservative, adjusting the optimal solution to maintain feasibility. [90]

$$\max c'x$$
$$s.t. \sum_{j} a_{ij}x_j + \sum_{j \in J_i} \hat{a}_{ij} y_j \leq b_i \quad \forall i$$
$$-y_j \leq x_j \leq y_j \quad \forall j \qquad (3)$$
$$l \leq x \leq u$$
$$y \geq 0$$

Although the Soyster method from 1973 offers the highest level of protection. In practice it is the most conservative. while robust solutions are more resilient, in general, to uncertainty and parameter change, they often have a worse objective function value compared to solutions obtained by standard linear optimization. A study in 2000 propose the following robust problem [91]:

$$\max c'x$$
$$s.t. \sum_{j} a_{ij}x_j + \sum_{j \in J_i} \hat{a}_{ij}{}^2 y_{ij} + \Omega_i \sqrt{\sum_{j \in J_i} \hat{a}_{ij}^2 z_{ij}} \leq b_i \ \forall i$$
$$-y_j \leq x_j - z_{ij} \leq y_j \quad \forall j \qquad (4)$$
$$l \leq x \leq u$$
$$y \geq 0$$

Under the data uncertainty model, the probability of violating constraint i is at most $exp(-\lambda_i^2/2)$. compared to Model (3), The Model (4) is robust and less conservative as every feasible solution for Model (4) is also viable for Model (3).

A new approach proposed a nonlinear formulation: [89]

$$\max c'x$$
$$s.t. \sum_{j} a_{ij}x_j + \max_{\{S_i \cup \{t_i\} | S_i \subseteq J_i, |S_i| = \lfloor \Gamma_i \rfloor, t_i \in J_i \setminus S_i\}} \{\sum_{j \in S_i} \hat{a}_{ij} y_j + (\Gamma_i - \lfloor \Gamma_i \rfloor) \hat{a}_{it_i} y_t\} \leq b_i \quad \forall i$$
$$-y_j \leq x_j \leq y_j \quad \forall j \qquad (5)$$
$$l \leq x \leq u$$
$$y \geq 0$$

For the ith constraint of the standard problem, the expression $a'_i x \leq b_i$ *is considered . here,* J_i represents the set of coefficients a_{ij}, *with* $j \in J_i$, which are subject to parameter uncertainty; in this scenario, $\tilde{a}_{ij}$, $j \in J_i$ fluctuates within a symmetric distribution centered around the nominal coefficient a_{ij}within the bounds $[a_{ij} - \hat{a}_{ij}, a_{ij} + \hat{a}_{ij}]$. A parameter Γ_i is introduced for each i as a robustness budget, which takes values in [0, | J_i and serves to modulate the robustness of the methodology relative to the conservatism of the resulting solution. Practically, it's improbable that every a_{ij}, $j \in J_i$, will vary simultaneously. The objective is to protect the solution against scenarios where up to $\lfloor \Gamma_i \rfloor$ of these coefficients might alter, specifically one coefficient a_{it} changes by $(\Gamma_i - \lfloor \Gamma_i \rfloor)\hat{a}_{it}$. In other words, the nature will only allow a subset of the coefficients to change to adversely affect the solution. In this case, the robust solution will certainly be feasible. Furthermore, the robust solution maintains a high probability of feasibility even if the extent of changes surpasses $\lfloor \Gamma_i \rfloor$.

A linear formulation of the model is:

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$$\boldsymbol{\beta_i(x^*,\Gamma_i) = max\sum_{j\in J_i} \hat{a}_{ij}|x_j^*|z_{ij}\ s.t. \sum_{j\in J_i} z_{ij} \leq \Gamma_i, i \leq z_{ij} \leq 1\ \forall j \in J_i} \quad (6)$$

If $\lfloor \Gamma_i \rfloor$ takes an integer value, constraint i will be protected by the following expression:

$$\boldsymbol{\beta_i(x^*,\Gamma_i) = \max_{\{S_i|S_i\subseteq J_i, S_i|=\Gamma_i\}}\{\sum_{j\in S_i} a'_{ij}|x_j|\}} \quad (7)$$

By using the duality form and applying it to model (2), we get the following linear model:

$$\boldsymbol{max\theta_0}\text{s.t.} \sum_{i=1}^{m} \boldsymbol{v_i x_{i0} = 1}, \sum_{r=1}^{s} \boldsymbol{u_r y_{r0} - \theta_0 - \Gamma_0 p_0} - \sum_{j\in J_0} \boldsymbol{q_{i_0} \geq 0}$$

$$\sum_{i=1}^{m} \boldsymbol{v_i x_{ij}} - \sum_{r=1}^{s} \boldsymbol{u_r y_{rj} - \Gamma_j p_j} - \sum_{j\in J_i} \boldsymbol{q_{ij} \geq 0},$$

$$\boldsymbol{\forall j p_j + q_{ij} \geq e_{y_{rj}} z_r \forall ij} \quad (8)$$

$$\boldsymbol{-z_r \leq u_r \leq z_r \forall\ r}$$

$$\boldsymbol{p_j q_{ij} \geq 0\ \ \forall i, j}$$

$$\boldsymbol{\mu_r, v_i \geq 0, \forall r, i}$$

where p_j and q_{rj} are dual variables, e_{ij}represent percentage of perturbation in a_{ij} and z the efficiency of risk under consideration.

In this study, the model is solved with Pulp python library for linear programing and python solver.

3.2. ML APPLICATION

Supervised learning algorithms allow machine learning models to learn autonomously from a set of data. Among the many models developed recently are artificial neural networks. Through the input layer, it receives a data sample, then undergoes operations with activation functions in the hidden layers, and finally produces a corresponding target category through its output layer [25,93].

Figure 2, illustrates a basic structure of an artificial neural network (ANN). It includes the neural connections, the biases allocated to each neuron, and the weights assigned to these connections, depicting a multi-layer model [25]. Neuron k is defined by two equations [94]:

$$\boldsymbol{y_k = f(u_k + b_k)} \quad (9)$$

$$\boldsymbol{u_k = \sum_i^N u_{ki} x_i} \quad (10)$$

Where $x_1, x_2, ..., x_n$ is the set of inputs and $w_{k1}, x_{k2}, ..., x_{kn}$ the neuron weights, u_k is the computation outcome of weights inputs, b_k is the bias term, f is the activation function and y_k is the output.

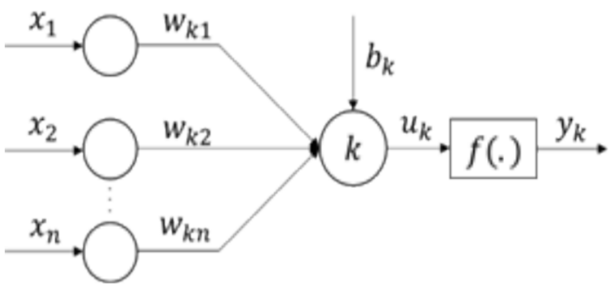

Figure 2. Architecture of a neural network.

In this research, N risks are analyzed, where each risk j is characterized by five inputs (O, S, D, BDCOST, BDDURATION). Additionally, each risk j is associated with a target variable, which is the score determined through RDEA. The combination of the weighted inputs and the RDEA score forms a mapping relationship via an activation function. y examining N risks with specified inputs and

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corresponding RDEA score outputs, the weights and the bias term can be identified using equations (9) and (10) throughout the model training process. [25].

In this study a Random Forest Regressor with 100 trees was used to predict the RDEA scores from the input features. Using a random seed for reproducibility, the dataset was split into training 90% and test 10%. We configured A Multi-Layer Perceptron Regressor to determine its architecture dynamically with an optimization through Particle Swarm Optimization (PSO). The mean squared error (MSE) of predictions aimed to minimize on the test set based on the PSO, by adjusting the number of neurons and learning rate of the MLP. The PSO was implemented with social and specific cognitive parameters who optimize the configuration of the MLP model. To ensure computational efficiency, The search space was constrained to [1,100] for the number of neurons.

4. Case study

The proposed approach, shown in Figure 3, was implemented in a plastic injection company operating in the automotive sector with the aim of obtaining a robust score for process risks in order to redesign and enhance performance. Initially, the BPR team was formed, incorporating members of the AMDEC PROCESS team. Based on the existing AMDEC register, costs and process downtime were determined as scores according to the approach defined in Table 2.

Table 2. Score of outputs cost and duration.

Score	BD-COST (euro)	BD-DURATION (day)
1	≤100	≤1
2	]100,500]	]1,3]
3	]500,3000]	]3,5]
4	]3000,6000]	]5,6]
5	>6000	>6

Potential process risks identified during the execution of the BPR method were added to the already defined risks. The primary goal of BPR is to reduce costs and delays, which is why these will not be considered as desirable outputs for DEA but rather as undesirable outputs [95]. The new values for outputs according to the Seiford and Zhu approach are calculated and presented in Table 3. The three approaches—RPN, Conventional DEA, and RDEA—will be applied and compared. The proposed ML model will be applied with the role of predicting new scores in case of improvements applied and also predicting scores for new risks.

Table 3. outputs undesirable values.

S	O	D	BD-COST	BD-DURATION	INDESIRABLE BD-COST	INDESIRABLE BD-DURATION
6	6	3	1	1	428	155
9	2	2	1	1	440	182
8	2	2	1	2	440	182
8	2	2	1	1	443	179
8	2	2	1	1	443	179
8	2	2	3	2	433	180
8	2	2	1	1	443	179
8	2	2	1	1	443	179
9	2	2	1	1	440	182
9	2	2	1	1	440	182
6	2	3	3	4	302	107
6	2	3	3	4	302	107

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6	2	3	4	4	433	182
6	2	2	1	1	424	180
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
9	2	2	1	1	440	182
8	2	2	1	1	443	179
8	2	2	1	1	443	179
9	2	2	1	1	440	182
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	3	1	302	107
6	2	3	4	2	255	125
6	2	3	3	1	349	131
6	2	2	1	1	424	180
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	1	1	427	173
6	2	3	5	3	427	173
6	2	3	4	2	255	125
6	3	3	1	1	417	173
9	2	3	3	2	437	173
6	2	3	5	3	423	173
6	2	3	4	2	417	169
6	7	5	4	2	418	170
9	3	5	5	2	412	171
9	2	10	5	3	477	123
9	2	2	5	3	447	73

It's important to note that the FMEA method is initially designed for preventive measures. Therefore, some process risks may not manifest within an organization. Additionally, the costs and duration of treatments can vary based on individuals' physical and mental conditions. As a result, the output values of the DEA model, established from field studies under the supervision of BPR-TEAM and PFMEA-TEAM, contain a degree of uncertainty. Due to this data uncertainty, using conventional DEA for evaluating and prioritizing risks is considered unreliable. Therefore, to accommodate data uncertainty, enhance solution robustness, and address the limitations of the RPN score, adopting the score based on the PFMEA-RDEA method to classify risk is a recommendation.

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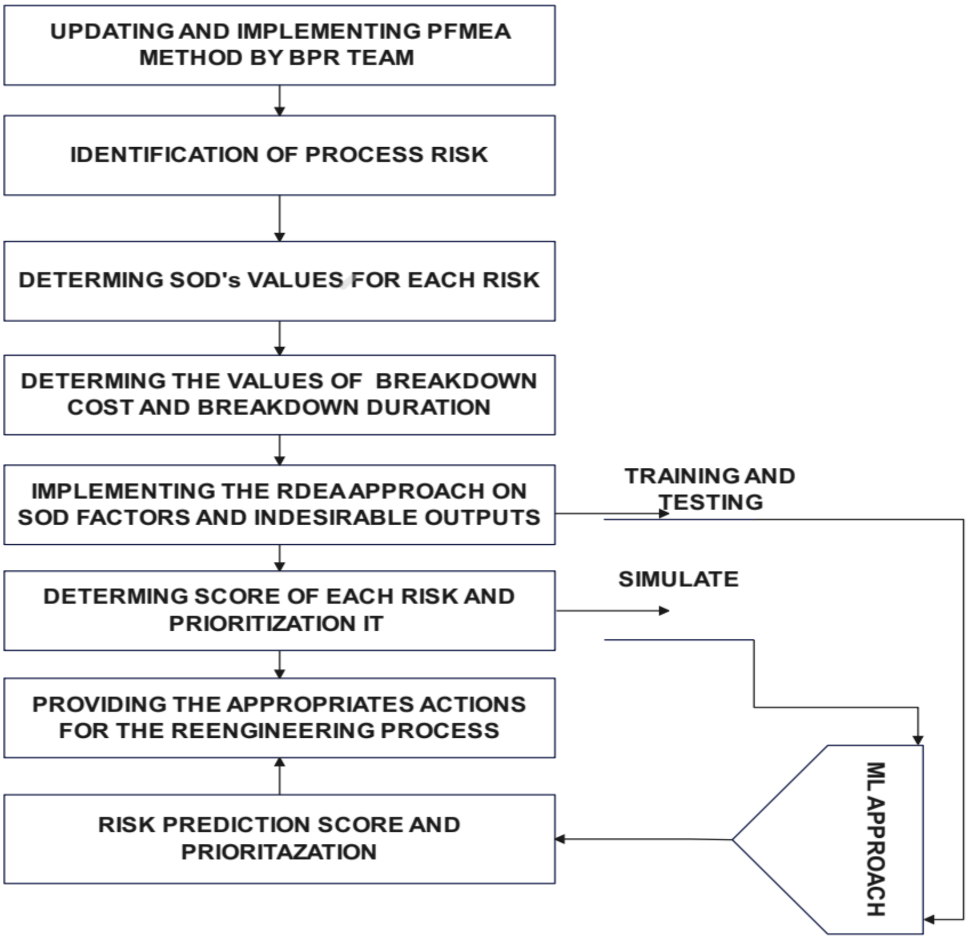

Figure 3. Proposed Approach.

To apply RDEA effectively, it is essential first to set the values of Γ_i (j = 1, 2, …, n) and Γ_0 for each constraint. When a constraint experiences less uncertainty, complete protection becomes crucial. Given that uncertainty impacts both output parameters across all constraints, the values of Γ_i (j = 1, 2, …, n) and Γ_0 are established at 2 to guarantee comprehensive protection against this uncertainty. In such cases, if all parameters shift to their least favorable conditions, the model remains fully protected against uncertainties.

The regression model to predict values is implemented using Python and several machine learning libraries.' sklearn.model_selection' is used to split the data into training and testing sets. 'sklearn.ensemble' imports the RandomForestRegressor. 'numpy 'is a library for advanced numerical operations. 'sklearn.neural_network' imports the MLPRegressor. 'pyswarms' is a library for particle swarm optimization, used here to optimize the hyperparameters of the neural network.

5. Results

To categorize process risks, the methods PFMEA, DEA-PFMEA, and RDEA-PFMEA are each applied independently. The traditional FMEA method ranks risks by using RPN scores, which are calculated by multiplying the input values from Table 3 and considering only the S-O-D values for the final scores. Table 4 shows the prioritization of identified risks based on these RPN scores.

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Table 4. Risk Prioritization by using PFMEA-RDEA Approach.

Risks	RPN		Conventional DEA		RDEA(e1=e2=0.5)		RDEA(e1=0.3e2=0.4)	
	Score	Priority	Score	Priority	Score	Priority	Score	Priority
R1	108	4	0.87	53	0.9000000000000004	52	0.8500000000000003	21
R2	36	7	0.77	22		22	0.8800000000000001	28
R3	32	45	0.65	13	0.8300000000000001	6	0.4499999999999996	6
R4	32	45	0.65	13		13	0.8499999999999999	15
R5	32	45	0.65	13		13	0.8499999999999999	15
R6	32	45	0.89	54	0.5	20	0.8700000000000003	25
R7	32	45	0.65	13	0.7999999999999998	13	0.8499999999999999	15
R8	32	45	0.65	13		13	0.8499999999999999	15
R9	36	7	0.77	22	0.7999999999999998	22	0.8800000000000001	28
R10	36	7	0.77	22		22	0.8800000000000001	28
R11	36	7	0.18	2	0.8200000000000003	1	0.002520000000012157	1
R12	36	7	0.18	2		1	0.002520000000012157	1
R13	36	7	0.45	8	0.7999999999999998	5	0.2499999999999993	5
R14	24	53	0.38	6		10	0.8199999999999996	12
R15	36	7	0.81	29	0.7999999999999998	30	0.8999999999999986	33
R16	36	7	0.81	29		30	0.8999999999999986	33
R17	36	7	0.81	29	0.8300000000000001	30	0.8999999999999986	33
R18	36	7	0.81	29		30	0.8999999999999986	33
R19	36	7	0.81	29	0.8300000000000001	30	0.8999999999999986	33
R20	36	7	0.81	29		30	0.8999999999999986	33
R21	36	7	0.81	29	0.05252000000000123	30	0.8999999999999986	33
R22	36	7	0.81	29		30	0.8999999999999986	33
R23	36	7	0.81	29		30	0.8999999999999986	33
R24	36	7	0.81	29	0.0525200000000123	30	0.8999999999999986	33
R25	36	7	0.81	29	0.1999999999999993	30	0.8999999999999986	33
R26	36	7	0.81	29		30	0.8999999999999986	33
R27	36	7	0.81	29	0.7699999999999996	30	0.8999999999999986	33
R28	36	7	0.77	22		22	0.8800000000000001	28
R29	32	45	0.65	13		13	0.8499999999999999	15
R30	32	45	0.65	13	0.8999999999999986	13	0.8499999999999999	15
R31	36	7	0.77	22	0.8999999999999986	22	0.8800000000000001	28
R32	36	7	0.81	29		30	0.8999999999999986	33
R33	36	7	0.81	29	0.8999999999999986	30	0.8999999999999986	33
R34	36	7	0.81	29		30	0.8999999999999986	33
R35	36	7	0.18	2	0.8999999999999986	1	0.002520000000012157	1
R36	36	7	0.57	10		53	0.8699999999999999	22
R37	36	7	0.23	5	0.8999999999999986	1	0.002520000000012157	1
R38	24	53	0.38	6		10	0.8199999999999996	12
R39	36	7	0.81	29	0.8999999999999986	30	0.8999999999999986	33
R40	36	7	0.81	29		30	0.8999999999999986	33
R41	36	7	0.81	29	0.8999999999999986	30	0.8999999999999986	33
R42	36	7	0.81	29		30	0.8999999999999986	33
R43	36	7	0.81	29	0.8999999999999986	30	0.8999999999999986	33
R44	36	7	0.81	29		30	0.8999999999999986	33
R45	36	7	0.8077	27	0.8999999999999986	28	0.8769999999999989	25
R46	36	7	0.5700	10		53	0.8699999999999999	22
R47	54	5	0.8541	52		27	0.8655000000000008	22

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R48	54	5	0.71	20	0.899999999999	9	0.7403200000000005	9
R49	36	7	0.8077	27	9986	28	0.8769999999999989	25
R50	36	7	0.09998	1	0.899999999999	8	0.6589999999999989	8
R51	210	1	0.71	20	9986	20	0.8240000000000016	14
R52	135	3	0.6	12	0.899999999999	19	0.8000000000000007	11
R53	180	2	0.54381	9	9986	10	0.7654899999999998	10
R54	36	7	0.843221	51	0.899999999999	7	0.5413899999999998	7
					9986			
					0.830000000000			
					0001			
					0.799999999999			
					9998			
					0.799999999999			
					9998			
					0.830000000000			
					0001			
					0.899999999999			
					9986			
					0.8999999999999986			
					0.8999999999999986			
					0.052520000000			
					00123			
					0.919999999999			
					9999			
					0.052520000000			
					00123			
					0.769999999999			
					9996			
					0.899999999999			
					9986			
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					0.899999999999			
					9986			
					0.8769999999999989			
					0.919999999999			
					9999			
					0.865500000000			
					0008			
					0.740320000000			
					0005			
					0.876999999999			
					9989			

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0.658999999999 9989
0.824000000000 0016
0.800000000000 0007
0.765489999999 9998
0.541389999999 9998

Based on the RPN score, as shown in the table, risk 51 with an RPN of 210 has the highest priority, followed by risks 52, 53, and 4, with RPN scores of 180, 135, and 108, respectively. Risks 14 and 38 have the lowest priority, each with a score of 24. By adding the outputs BD-COTS and BD-DURATION to the three inputs S-O-D, and applying the DEA-PFMEA approach with undesirable outputs, a different priority ranking is generated, the priority of risk 51 becomes 20, while risks 52, 53, and 54 receive the following priorities: 12, 9, and 53 respectively. As for risks 14 and 38, they become more prioritized, ranking at 6. With this approach the first priority is related to risk 50 followed by risks 11 and 12. Now the lowest priority is related to risk 1, this shows the effect of breakdown cost and the breakdown duration. The comparison between the priorities of RPN scores and DEA-PFMEA scores is presented in the following figure.

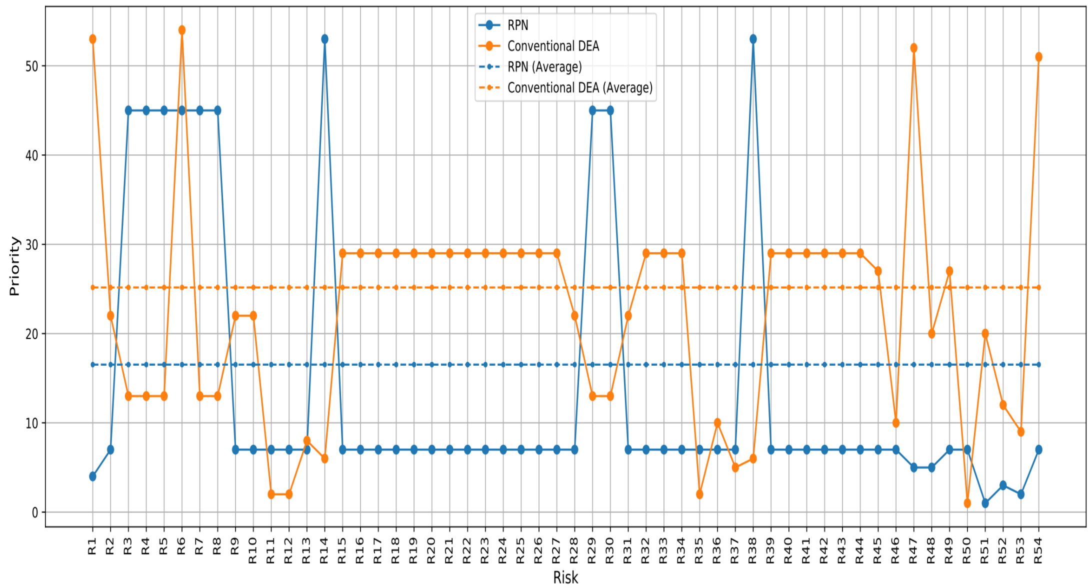

Figure 4. Prioritization based on score of PFMEA-DEA approach and RPN score.

In the following step, the perturbation level should be considered for outputs. Initially, this is applied to two outputs of the RDEA model withe1 = e2 = 0.5, **l**ater, the perturbation levels are set to $\boldsymbol{e_1} = \mathbf{0.3}$ and $\boldsymbol{e_2} = \mathbf{0.4}$. The initial percentages are chosen randomly to demonstrate the effect of perturbation on the outputs. The latter percentages were selected and approved by the FMEA and BPR team involved in this study.

As Table 4 shows, the order of priorities has changed, demonstrating the strong impact of uncertainty on the data, represented by the percentages of perturbations on the undesirable outputs of the system. Risks 11, 12, 35, and 37 become the highest priority, followed by other risks. Another advantage is that the classification categories have been reduced, providing a clearer picture of the project's risk status. This serves as a more robust decision-making tool for redesigning the studied process, thereby planning the necessary action plan to address these risks and enhance the process's performance, aligning with the initial goal of the BPR method.

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The following figures present comparisons of the scores obtained by the different approaches applied in this study.

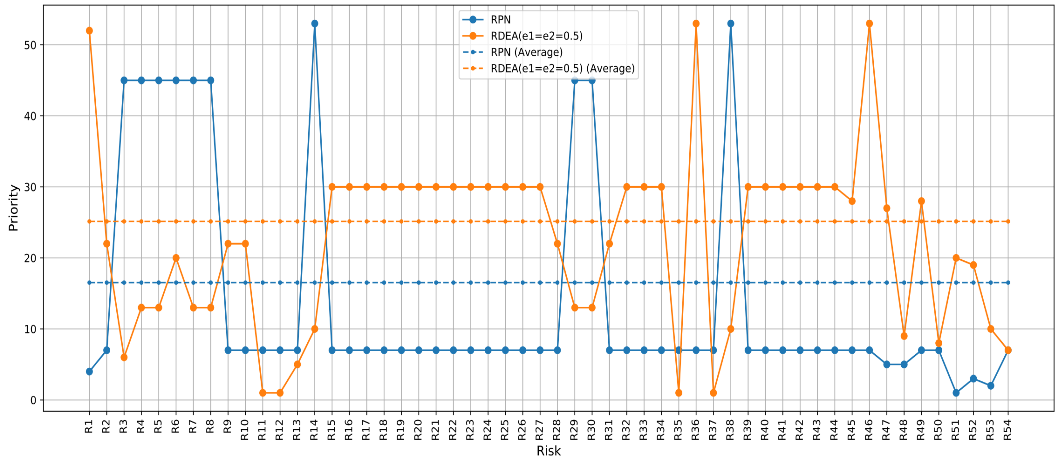

Figure 5. Prioritization based on score of PFMEA-RDEA approach and RPN score.

There's a significant volatility in the RPN scores, which could indicate that this method is highly sensitive to the specific risk factors for each risk. The PFMEA-RDEA method appears more conservative, potentially smoothing out extreme variations seen in RPN due to its consideration of perturbations in the model.

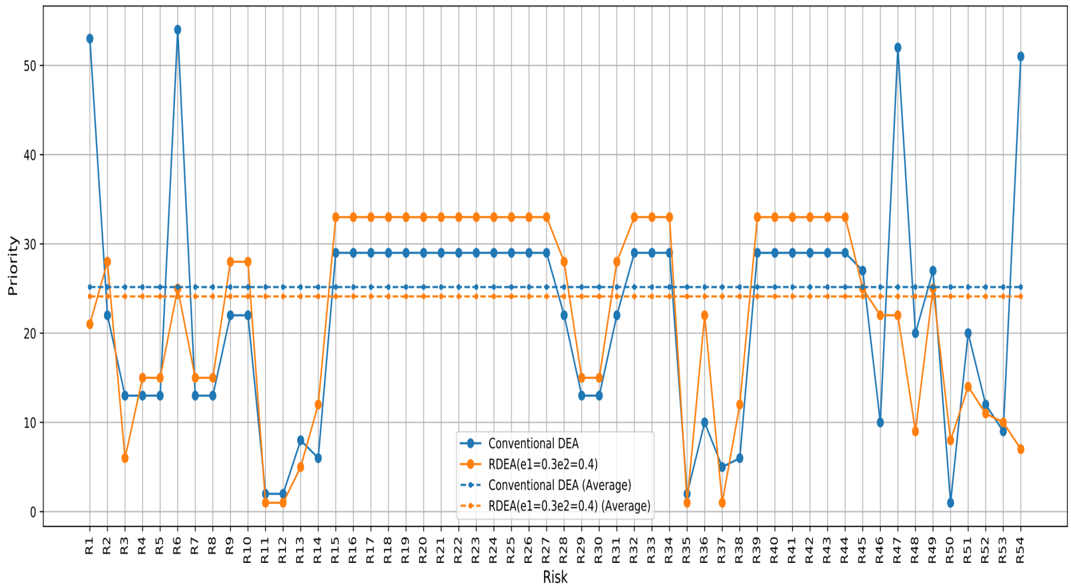

Figure 6. Prioritization based on score of PFMEA-RDEA approach and PFMEA-DEA score.

The conventional PFMEA-DEA method shows substantial fluctuations in risk priorities. The PFMEA-RDEA method, with specific perturbation percentage, provides a more moderate distribution of risk priorities. This method does not reach as high as the conventional PFMEA- DEA in most cases, suggesting a more tempered response to the perceived risk severity.

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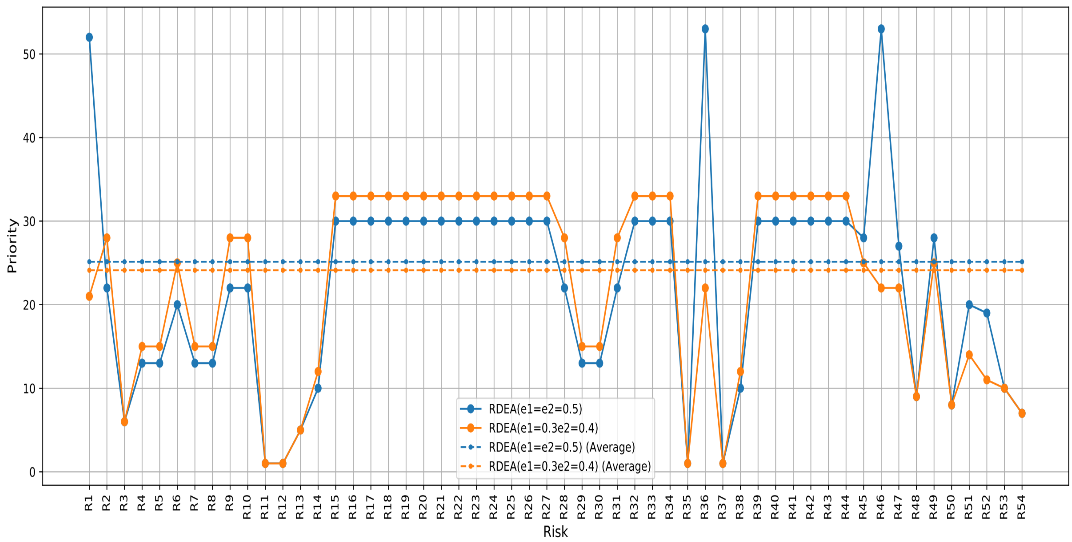

Figure 7. Prioritization based on score of PFMEA-RDEA approach score with different perturbation percentage.

This comparison highlights how small changes in perturbation parameters within the same methodological framework can lead to different prioritizations of risks. This could influence strategic decisions in environments where understanding and mitigating risks are crucial for operational performance and efficiency.

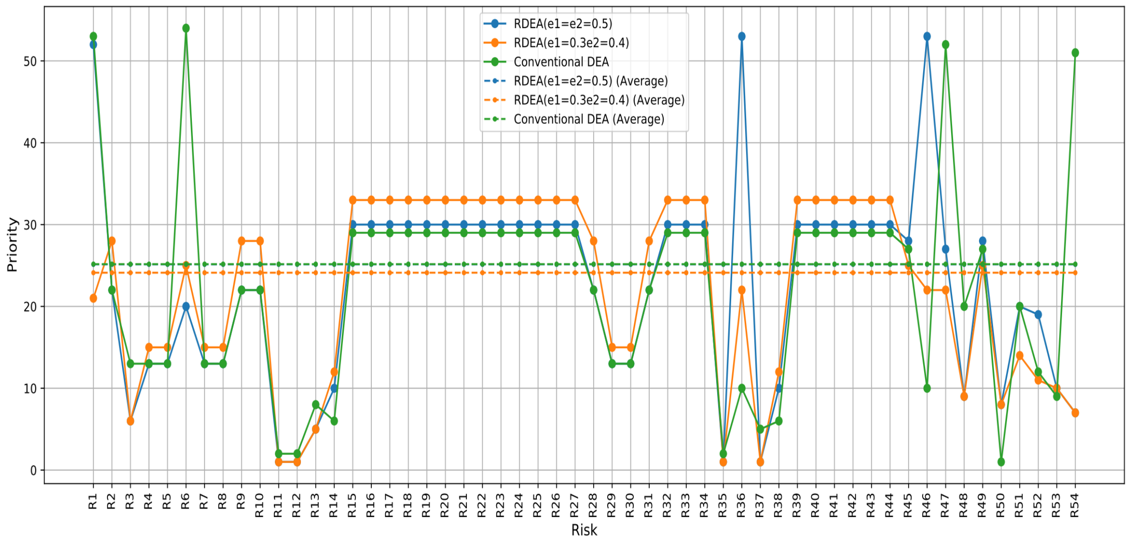

Figure 8. Prioritization of risks based on score of PFMEA-DEA and PFMEA-RDEA approach score with different perturbation percentage.

The comparison of these risk assessment methods illustrates how each method interprets and prioritizes risks differently based on its underlying assumptions and calculations. The RPN method tends to highlight risks more dramatically. In contrast, a more balanced and potentially more realistic view of risk priorities is offered by the approach PFMEA- DEA and PFMEA-RDEA methods offer a more balanced and potentially more realistic view of risk priorities, suitable for environments where resources must be allocated efficiently.

Table 5. The average efficiency scores based on the criteria.

RDEA Score	ML Score	ERROR
0.8500000000000003	0.8514999999999994	0.001

0.8800000000000001	0.8804196522776031	0.0004
0.44999999999999996	0.4746742857142863	0.02
0.8499999999999999	0.8628437016205744	0.01
0.8700000000000003	0.8658000000000005	0.005
0.8800000000000001	0.8804196522776031	0.0005
0.8800000000000001	0.8804196522776031	0.0005
0.0025200000000012157	0.0049948000000000015	0.002
0.24999999999999993	0.2475252	0.002
0.8199999999999996	0.8423190166500167	0.01
0.8999999999999986	0.8398135963221486	0.05

Using the proposed ANN model, the obtained MSE is 0.002145834611031225, which indicates high performance. Therefore, the designed artificial neural network model is useful for prediction purposes. The main goal of this study is to develop methods to predict modified risk values when process reengineering strategies are implemented. This allows for the generation of new scores that aid in managing the BPR project to avoid surprises.

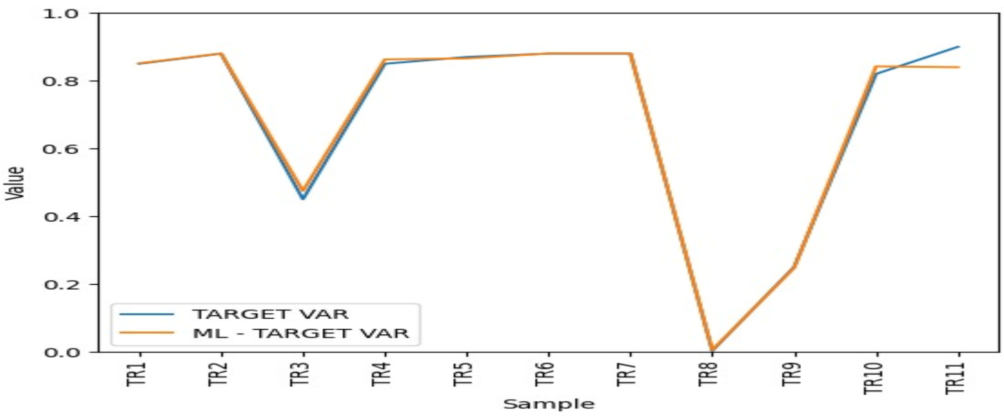

Figure 9. The average ML efficiency scores.

There is a high degree of overlap between the two lines, indicating a good general agreement between the predicted and actual values across most samples. The close tracking between the predicted and actual values in most parts of the graph suggests that the machine learning model is performing well. However, the instances of under-prediction are due to insufficiency of training data.

6. Discussion and Conclusion

This study introduces a new integrated risk analysis approach PFMEA-RDEA-ML, designed to prioritize process risks in a Business Process Reengineering project by introducing BD-COST and BD-DURATION as undesirable outputs to the conventional PFMEA-DEA system. This pushes the analysis to another dimension, allowing for the consideration of uncertainty by integrating coefficients of perturbation on the parameter values of the system, typically based on expert judgment.

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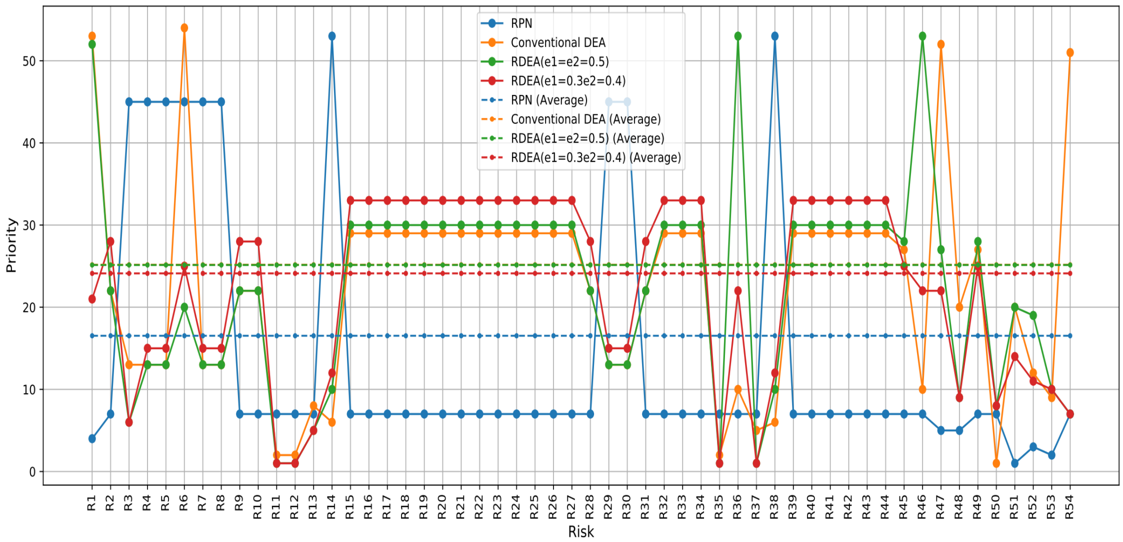

Figure 10. Average efficiency scores of the proposed approaches.

As mentioned in the literature review, over 70% of projects fail, and among the reasons are the inapplicability of management strategies, including RM, as well as the failure to consider various factors during the analysis; as shown in the figure, risk prioritization using the RPN approach differs completely from prioritization according to other approaches. This approach enables decision-makers to have a clearer and more multidimensional view of process management and reengineering, given the verified relationship of added parameters with operational performance. Additionally, the rapid development of machine learning prediction algorithms provides the possibility of continuous execution of this approach, thus allowing for the automatic generation of new scores and priorities once partial or complete reengineering actions of processes have been established. The application of this approach in a company operating in the highly competitive automotive sector has highlighted the distinction and observation of the effect of integrating new parameters in risk analysis and also the perception of the uncertainty effect modeled by the disturbance percentages in the RDEA model.

Author Contributions: Conceptualization, R.H. and M.M. and L.A.; methodology R.H. and M.M. and L.A.; software, R.H. and M.M. and L.A.; validation, R.H. and M.M. and L.A.; formal analysis R.H. and M.M. and L.A.; investigation, R.H. and M.M. and L.A.; resources, R.H. and M.M. and L.A.; data curation, R.H. and M.M. and L.A.; writing—original draft preparation, R.H.; writing—review and editing, R.H. and M.M. and L.A.; visualization, R.H.; supervision, M.M. and L.A.; project administration, M.M. and L.A.; funding acquisition, R.H. and M.M. and L.A. All authors have read and agreed to the published version of the manuscript.

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