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Advancing Risk Assessment in Renewable Power Plant Construction: an Integrated DEA-SVM Approach

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Abstract

An indispensable aspect of human life is energy. The escalating global population and the subsequent rise in the human need for energy, coupled with the constraints of fossil fuels, have compelled researchers to explore innovative techniques for energy production and the adoption of renewable energy sources. The construction of renewable power plants emerges as a paramount solution for achieving clean energy, a strategy successfully implemented in various countries globally, including India, China, the USA, Central Asian nations, and Africa. Strategically located and blessed with significant solar potential, Iran is a promising candidate for establishing solar power plants. Despite its high potential for constructing solar power plants, Iran faces limitations that require careful consideration. Investing in renewable power plant projects in Iran necessitates addressing various risks and uncertainties. This paper introduces an innovative approach to assessing the risks associated with solar power plants, utilizing an integrated method that combines Data Envelopment Analysis (DEA) and Support Vector Machine (SVM). In the initial phase, DEA cross-efficiency measures risk factors derived from Failure Modes and Effects Analysis (FMEA). This approach not only overcomes certain drawbacks of FMEA but also eliminates several limitations of DEA, enhancing the discrimination capability for decision units. Subsequently, a SVM is developed to monitor the process, concluding with tailored risk treatment and monitoring processes specifically designed for the unique context of Iran's solar energy landscape.

Keywords: Cross efficiency, Power plant, Failure modes and effects analysis, Risk, Support vector machine.

1 | Introduction

Approximately 60% of total greenhouse gas emissions, the primary contributors to the warming effect, result from the world's significant reliance on fossil fuels for energy demand [1]. In 2015, the Paris Climate Agreement was established to combat climate change, with many European countries aiming for 100% renewable electricity by 2050, as outlined in the 2019 European Green Deal. As an abundant and clean energy source, solar power is crucial in renewable energy [2]. Technological advancements have decreased the cost of renewable power plants from 1980 to 2019 [3]. However, stable prices for electricity from fossil fuels have kept renewable power competitive in numerous regions globally or are anticipated to do so in the near future [4].

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Today's dynamic financial and organizational landscapes necessitate effective responses to numerous uncertainties. Risk management is a valuable approach to preparing for and addressing risks and their consequences. The initial steps in risk management involve identifying and evaluating risk factors.

The overall risk management process encompasses four principal sub-processes: 1) risk definition, 2) risk evaluation and analysis, 3) risk treatment, and finally, and 4) risk monitoring [5]–[7]. Risk identification is the first process, pinpointing actions with adverse impacts on operational objectives. Risk assessment combines the sub-processes of risk analysis and evaluation, distinguishing each risk and its consequences. Risk treatment involves plan design, selection, and implementation, which is crucial for selecting fitting strategies.

Quantitative and qualitative approaches proposed by researchers are related to risk identification and assessment processes. While both approaches offer practical recommendations[8], the quantitative approach is preferred when sufficient data is available. However, due to the often unavailability of quantitative data in real-world problems, integrated models like Multiple Criteria Decision-Making (MCDM) have been employed in risk management literature. Failure Modes and Effects Analysis (FMEA), a widely used qualitative approach, assigns a Risk Priority Number (RPN) to failure modes, with a higher RPN indicating greater urgency. The RPN is calculated by multiplying the FMEA inputs: Occurrence (O), denoting the frequency of failure; Severity (S), indicating the seriousness of the failure's effect; and Detect (D), reflecting the probability of detecting the failure before its outcome [9].

In the risk management literature, noteworthy limitations are associated with using crisp values to calculate RPNs in FMEA. Some of these limitations include:

I. Non-Intuitive Statistical Properties: The multiplication of Occurrence (O), Severity (S), and Detectability (D) to calculate the RPN index may result in non-intuitive statistical properties. Different combinations of O, S, and D might yield identical RPN values, potentially leading to a misinterpretation of risk implications and, consequently, a waste of resources and time [10].

II. Questionable Mathematical Representation: The mathematical representation for computing the RPN index is considered questionable, lacking a clear rationale for why the multiplication of O, S, and D produces the RPN.

III. Neglect of Relationships and Equal Weighting: The RPN index does not consider direct and indirect relationships among failure modes. Additionally, it presumes that the three risk factors (O, S, and D) are equally important, making it inadequate for systems with multiple subsystems [11].

IV. Difficulty in Precise Evaluation: Precisely evaluating the three risk factors (O, S, and D) can be challenging.

V. Interpretation Differences in RPN Values: Differences in interpreting RPN values across various ranges may not be consistent. For instance, the distinction between RPNs of 5 and 10 may not be equivalent to or less than the difference between 950 and 1000.

To address these drawbacks, this paper proposes the application of Data Envelopment Analysis (DEA). DEA models can measure the weights of risk factors and consider relationships among failure modes. The subsequent subsection reviews pertinent studies in the risk management literature.

2 | Literature Review

DEA is a widely used quantitative method for assessing the efficiency and performance of Decision-Making Units (DMUs) across various fields, ranging from finance and economics to healthcare and environmental management. The fundamental principle of DEA is to evaluate the relative efficiency of DMUs by considering their input and output relationships. DEA has gained significant attention due to its ability to handle multiple inputs and outputs simultaneously, making it a versatile tool for performance measurement.

Over the years, numerous scholars have contributed to developing and enhancing DEA models, each bringing unique perspectives and methodologies to address specific challenges. Scholars have proposed different variations of DEA models to accommodate various complexities and real-world scenarios. These models often differ in their mathematical formulations, application domains, and the treatment of uncertainties [10, 12–19].

Several scholars have integrated DEA into Failure Mode and Effects Analysis (FMEA), leveraging DEA's efficiency evaluation capabilities to enhance the prioritization and risk assessment of failure modes in various processes and systems. Rezaee et al. [11] introduced a synergized FMEA and DEA model, treating potential risks or failure modes in FMEA as DMUs, with O-S-D ratings of FMEA as inputs to the DEA models. Chin et al. [20] proposed an FMEA approach that applies DEA to prioritize the risk of failure modes, considering the relative importance weights of risk factors.

Sankar and Prabhu [21] introduced a modified approach for prioritizing failure modes within an FMEA system, assigning risk priority ranks (RPRs) between 1 and 1000. They represented the increasing risk of the 1000 possible combinations of Severity (S), Occurrence (O), and Detectability (D) from 1 to 1000. The RPRs, when organized in ascending order by experts, can be utilized as if–then rules, where a higher rank indicates a higher priority for failure.

Chang et al. [22] incorporated grey theory in RPN evaluation in FMEA. Utilizing fuzzy linguistic terms (Very Low, Low, Moderate, High, and Very High) to measure the values of O, S, and D, they applied grey relational analysis to prioritize failure modes and identify potential causes. Yang et al. [22] proposed a novel fuzzy rule-based Bayesian reasoning approach to rank failure modes in FMEA. Purdy [7] employed a fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to assess O, S, and D and their relative importance using triangular fuzzy numbers.

Shifting the focus to the business sector, machine learning algorithms have become prominent in risk management. Leo et al. [23] applied machine learning applications in risk management within the banking industry. Chandrinos et al. [24] proposed a machine learning-based approach for risk management in portfolio selection. Paltrinieri et al., in their study, applied a Deep Neural Network (DNN) for risk assessment in an Oil & Gas drilling rig. Gondia et al. [25] utilized machine learning for risk evaluation in the construction area, highlighting its predictive power in enabling evidence-based decisions and formulating suitable strategies in practical project risk management.

3 | Methodologies

3.1 | Data Envelopment Analysis

Suppose there is a set of n DMUs indexed by j (j = 1,…, n), and each DMU_j consumes m inputs denoted by x_{ij} $(i = 1, \dots, m)$ to produce s output, the outputs denoted by s_{rj} $(r = 1, \dots, s)$, Then, the efficiency score of each DMU under evaluation (DMU_o) is measured as

$$
\begin{aligned}
& max\theta = \sum_{r=1}^{s} u_r y_{ro}, \\
& s.t. \\
& \qquad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \\
& \qquad \textstyle\sum_{i=1}^{m} v_i x_{io} = 1, \\
& \qquad v_i, u_r \ge 0(\varepsilon).
\end{aligned} \tag{1}
$$

In the presented model, denoted by *Relation (1)*, ε represents a non-Archimedean infinitesimal. This model is an output-oriented DEA model, wherein the objective function and constraints aim to maximize outputs while maintaining inputs at their existing levels [26]. The optimal value of θ, denoted as θ*=1, occurs when the DMUo is positioned on the efficient frontier, rendering it CRS-efficient. Within DEA, the DMU transforms quantitative input values into outputs. As previously discussed, efficiency can be evaluated through an output-to-input ratio, reflecting productivity. This ratio serves as a useful metric for comparative purposes. When combining FMEA with DEA, Failure Modes align with DMUs, and the inputs of DMUs are represented by the values of O (Occurrence), S (Severity), and D (Detectability).

3.2 | Support Vector Machine

In this paper, we delve into the viability of utilizing a SVM algorithm for risk analysis (*Fig.1*). SVM, grounded in statistical learning theory, leverages supervised learning techniques. One notable feature of this model is its ability to mitigate the over-learning problem. The primary objective of SVM is to identify a function, f(x), for the training set, emphasizing the largest permissible bias. Consequently, higher biases are undesirable in pursuing optimal model performance [27].

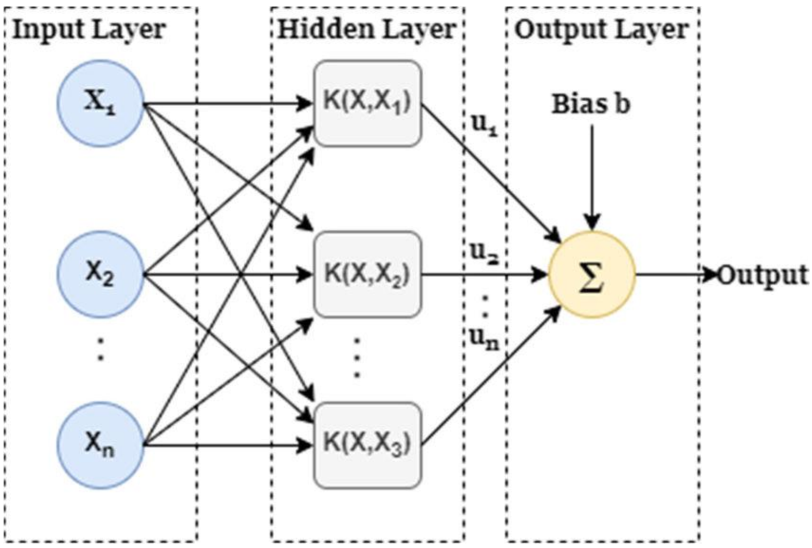

Fig. 1. The structure of SVM algorithm.

$$y = \sum_{i=1}^{N} \alpha_i - \alpha_i^*)K\ X_i, X) + b,$$

$$K\ X_i, X) = X_i X,$$

$$K\ X_i, X) = (1 + X_i X)^p\ , p = 2{,}3,$$

$$K\ X_i, X) = e^{-\gamma\|X_i - X_j\|^2},$$

where α_i and α_i^* are the Lagrange multipliers, and $K\ X_i, X)$ is the kernel function. In this paper, we evaluated the Gaussian kernel function as follows:

Two essential parameters in the SVM algorithm are the regularization parameter and the size of the error-insensitive zone (ε), both of which are typically determined using trial-and-error techniques.

3.3 | Performance Criteria

This study's assessment and comparison of machine learning models are pivotal. To gauge their effectiveness, we employ the Mean Absolute Error (MAE) [28], [29]. This metric serves as a measure of the average absolute differences between predicted and actual values. It provides valuable insights into how well the models perform in accuracy, offering a more nuanced understanding of their predictive capabilities. The lower the MAE, the closer the predictions align with the actual values, indicating higher accuracy and reliability in the models' performance evaluation.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|d_j - p\right| ,$$

where d_j indicates the i^{th} value of the real target for the j^{th} pattern, and p_j shows the predicted target for the j^{th} pattern.

Mean absolute error provides the average of the absolute values of errors across all records. This index reflects the average magnitude of errors, irrespective of their direction. It serves as a valuable criterion for evaluating the performance of the model. A lower MAE signifies a higher level of accuracy, indicating superior performance in predicting target values. The MAE is a robust measure to assess how well the model aligns with the actual values, contributing to a comprehensive evaluation of predictive capabilities.

4 | Dataset

A comprehensive review of risk management literature concerning the construction of solar, wind, and biomass power plants, experts have identified 19 criteria as particularly crucial. Given precedence over others, these criteria are meticulously documented in *Table 1*.

The risk analysis is conducted with the expertise of professionals who employ a 10-scale system to assess the probability of occurrence, detectability, and severity. The resulting scores for Occurrence (O), Severity (S), and Detectability (D) are meticulously outlined in *Table 1*. This dataset is a fundamental resource for an in-depth examination of risks associated with power plant construction, providing valuable insights into the nuanced evaluation of factors contributing to the overall risk landscape.

Table 1. Comprehensive assessment of occurrence, severity, and detectability scores.

Power Plant	Solar			Wind			Biomass		
Risk factors	O	S	D	O	S	D	O	S	D
Operating (C1)	3	2	2	4	6	6	8	6	3
Territory (C2)	2	3	2	7	4	2	6	6	4
Investment (C3)	6	6	4	5	7	3	3	5	8
Odor (C4)	2	8	8	2	4	8	4	6	6
Terror (C5)	4	7	5	2	6	6	3	4	3
Change of law (C6)	2	2	2	3	4	3	4	5	2
Design defect (C7)	3	8	6	3	5	3	5	6	5
Technology development (C8)	5	3	5	4	4	5	2	6	3
Incorrect material selection (C9)	2	7	6	2	6	3	2	1	1
Noise (C10)	2	2	2	2	3	3	1	1	2
Emission (C11)	1	1	2	1	1	2	1	2	2
Waste (C12)	1	2	2	1	2	2	4	3	2
Harm to living entities (C13)	1	2	2	2	2	3	2	4	2
Occupational accident (C14)	2	6	8	5	5	3	4	3	3
Failure during construction (C15)	2	2	3	4	3	4	4	4	3
Extending periodic maintenance time (C16)	3	4	3	4	4	3	4	4	6
Extension of construction time (C17)	3	5	6	4	4	6	3	5	7
Low productiveness (C18)	4	4	8	3	4	7	5	5	3
Workload for employee (C19)	3	6	3	2	4	4	4	3	3

5 | Innovative Approach: Utilizing DEA Efficiency Score

This paper introduces a novel approach by employing DEA efficiency scores as an alternative to the traditional RPN index for prioritizing failure modes, addressing the challenges elucidated in Section 1.

In the application of DEA, the risk factors Occurrence (O), Severity (S), and Detectability (D) are treated as inputs to DMUs, where each failure mode is considered as an individual DMU. A dummy output with a constant value of 1 is assigned to each DMU. The outcomes of both DEA scores and RPN indices are presented in detail in *Table 2*. This innovative methodology aims to provide a more nuanced and effective means of assessing and prioritizing failure modes, overcoming the limitations associated with traditional RPN values.

Table 2. DEA scores and RPN index regarding failure modes.

	Solar		Wind		Biomass	
Sub-criteria	EFF	RPN	EFF	RPN	EFF	RPN
C1	0.54	12	0.27	144	0.31	90
C2	0.68	12	0.31	56	0.25	144
C3	0.27	144	0.33	105	0.27	144
C4	0.31	128	0.31	64	0.26	120
C5	0.30	140	0.34	72	0.27	144
C6	0.68	8	0.45	36	0.45	36
C7	0.31	144	0.45	45	0.45	40
C8	0.27	75	0.30	80	0.27	150
C9	0.37	84	0.54	36	0.55	36
C10	0.68	8	0.55	18	0.92	2
C11	0.96	2	0.91	2	0.95	2
C12	0.95	4	0.91	4	0.95	4
C13	0.95	4	0.56	12	0.45	24
C14	0.31	96	0.96	75	0.68	16
C15	0.56	12	0.34	48	0.39	36
C16	0.45	36	0.38	48	0.38	48
C17	0.31	90	0.28	96	0.28	96
C18	0.24	128	0.29	84	0.29	105
C19	0.45	54	0.47	32	0.34	75

Examining *Table 2* reveals a noteworthy observation: certain failure modes exhibit distinct DEA scores despite having identical RPN values. This disparity underscores the added value of DEA in refining the prioritization of failure modes within FMEA. Notably, the failure mode with the lowest DEA score indicates the factor with the highest associated risk.

The results from the DEA scores indicate that the failure mode "Low Productiveness for Solar Power Plant Construction" holds the highest risk. Conversely, the failure mode with the lowest DEA score, signifying the highest risk, pertains to "Occupational Accident in the Construction of Wind Power Plant."

We observe variations when comparing these findings to those derived from the RPN index. According to the RPN index, failure modes such as "Investment" and "Design Defect for Construction of Solar Power Plants," as well as "Operating for Wind Power Plant" and "Territory," "Investment," and "Odor for Biomass Power Plant" are identified as having the highest associated risks.

This discrepancy emphasizes the nuanced insights provided by DEA, offering a more refined and context-specific assessment of risk in comparison to the traditional RPN approach.

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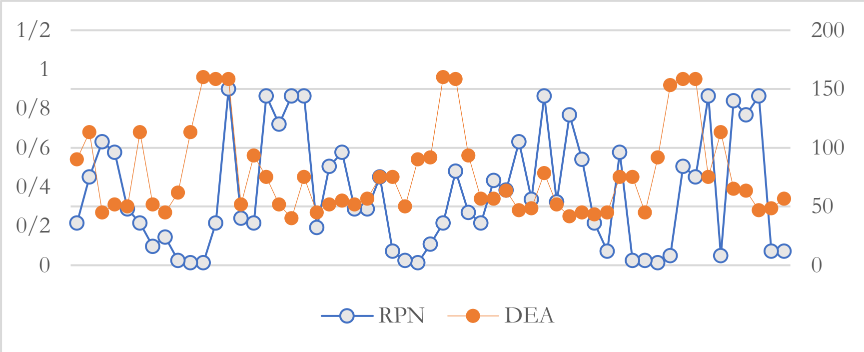

Fig. 2. Comparison of RPN value and DEA score.

6 | Integration of SVM for Precise Score Prediction

Following the computation of DEA scores for failure modes, the subsequent step involves applying the SVM approach to predict these scores. This predictive model is instrumental in addressing a limitation in DEA where changing the score of one Decision Making Unit (DMU) can impact the scores of others. The SVM prediction enables the calculation of precise improvement percentages for enhanced DMUs without necessitating adjustments to other DMUs' scores.

Given the varied outcomes associated with different SVM kernels, we conducted an extensive testing phase, assessing 10 distinct SVM models to identify the most effective one. Utilizing IBM SPSS MODELER, we explored various kernels, including sigmoid, RBF (with different gamma values), linear, and polynomial (with different degrees, gamma, and bias settings). The results conclusively point to the polynomial kernel with a degree of 3 as the optimal setting for SVM, displaying the highest correlation and the lowest Relative Error.

Notably, the implementation of SVM on the dataset reveals that the most influential predictor is Severity (S). *Fig. 3* visually represents the importance of risk factors as predictors. In this study, 70% of the data was allocated for training purposes, with the remaining 30% reserved for testing the SVM model's predictive accuracy. This rigorous methodology ensures robust model training and evaluation.

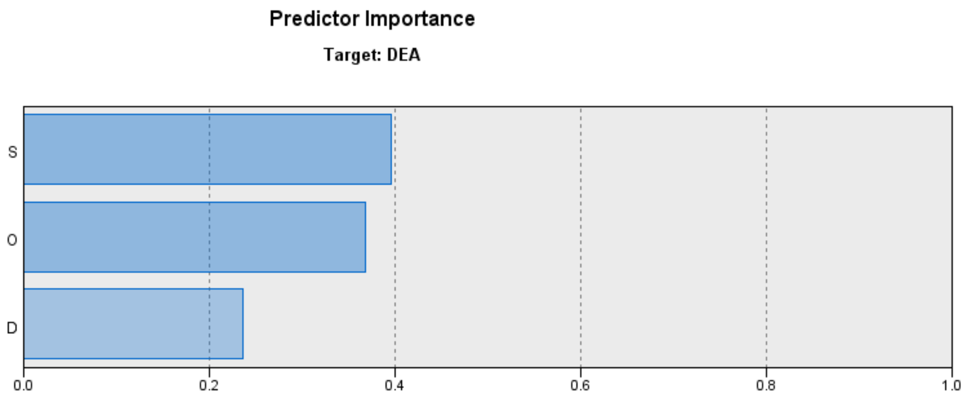

Fig. 3. Predictor importance of the risk factors.

The predicted values and real scores are represented in *Table 3*. Results show a high correlation between the target and predicted values. *Fig. 4* shows the scatterplot of DEA scores versus predicted scores.

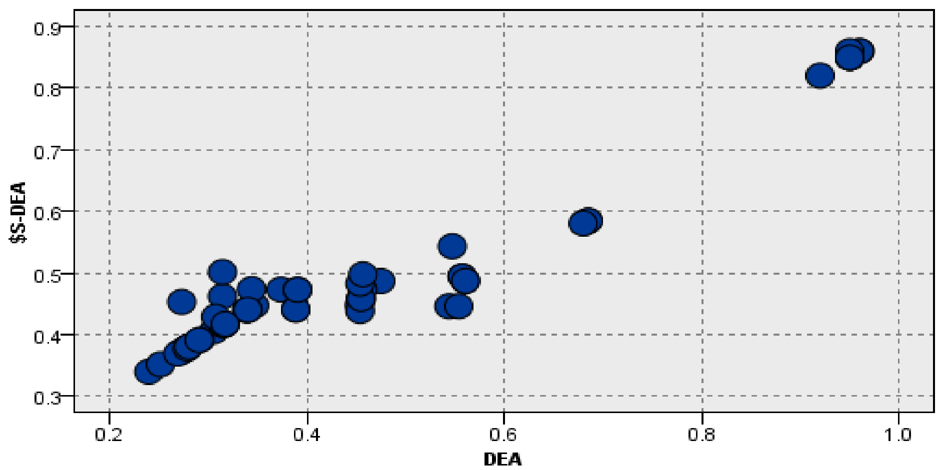

Fig. 4. The scatterplot of DEA scores versus predicted scores.

The comparison of the target and output of the SVM approach is represented in *Fig. 5*.

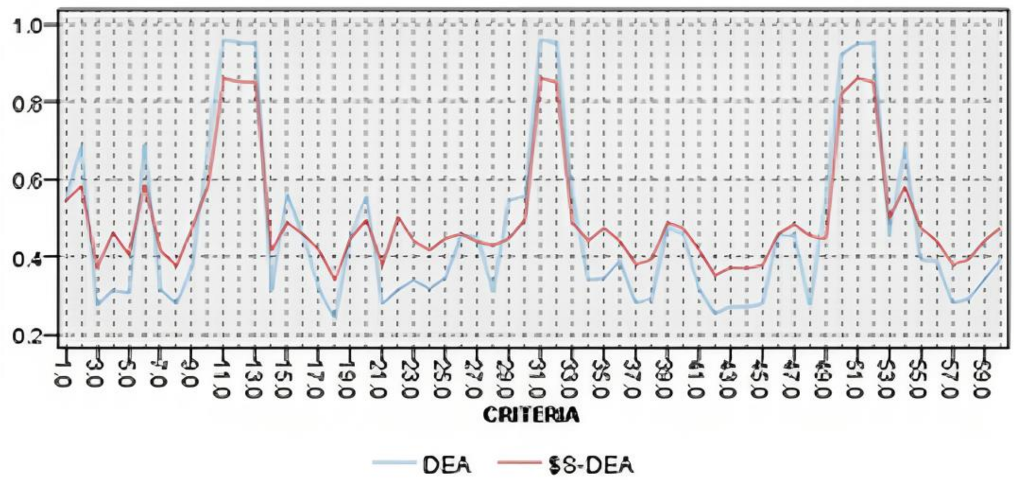

Fig. 5. Comparison of target and output of SVM approach.

The results of applying the SVM for the output field in DEA are summarized and compared in the table provided with traditional DEA. Here's an interpretation and discussion of the key metrics:

Minimum and maximum error

I. Training (1_Training): The minimum error observed during training is -0.1, indicating a slight underestimation, while the maximum error is 0.1, signifying a slight overestimation.
II. Testing (2_Testing): The minimum error in the testing phase is -0.202, suggesting a minor underestimation, while the maximum error is 0.11, implying a slight overestimation.

Mean error

I. Training: The mean error during training is -0.027, indicating a slight overall underestimation in the predicted values.
II. Testing: The mean error in the testing phase is -0.034, suggesting a slight underestimation of the predicted values.

Mean absolute error

Both in training and testing, the MAE is relatively low, with values of 0.084 and 0.083, respectively. This suggests that, on average, the absolute differences between the predicted and actual values are small.

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Standard deviation

The standard deviation during training is 0.085; in testing, it slightly increases to 0.096. This indicates moderate variability in the errors between the predicted and actual values.

Linear correlation

During training, the linear correlation is very high at 0.976, indicating a strong linear relationship between the predicted and actual values. In testing, the correlation remains high but decreases slightly to 0.912.

7 | Discussion

I. The results suggest that SVM-DEA generally provides accurate predictions, with mean errors close to zero and low MAEs.
II. The standard deviation implies some error variability, indicating that the model's performance may vary for different instances.
III. The high linear correlation in training indicates strong predictive capabilities, while a slightly lower correlation in testing might indicate differences in performance on new, unseen data.
IV. The occurrences metric hints at instances where SVM-DEA diverges from traditional DEA, emphasizing the need to consider specific cases where the models differ carefully.

In summary, the SVM-DEA model shows promise in accurately predicting DEA efficiency scores, with some variability in performance on testing data. Further analysis of specific instances where the models deviate could provide valuable insights into the strengths and limitations of the SVM-DEA approach.

Table 3. The values of target and predicted scores by SVM.

Sub-Criteria	DEA	SVM	DEA	SVM	DEA	SVM
C1	0.54	0.549	0.27	0.559	0.31	0.550
C2	0.68	0.676	0.31	0.254	0.25	0.456
C3	0.27	0.278	0.33	0.31	0.27	0.303
C4	0.31	0.382	0.31	0.343	0.26	0.254
C5	0.30	0.300	0.34	0.367	0.27	0.278
C6	0.68	0.685	0.45	0.332	0.45	0.272
C7	0.31	0.325	0.45	0.460	0.45	0.254
C8	0.27	0.280	0.30	0.461	0.27	0.460
C9	0.37	0.386	0.54	0.316	0.55	0.469
C10	0.68	0.685	0.55	0.537	0.92	0.245
C11	0.96	0.959	0.96	0.559	0.95	0.537
C12	0.95	0.939	0.95	0.959	0.95	0.96
C13	0.95	0.939	0.56	0.939	0.45	0.959
C14	0.31	0.334	0.34	0.561	0.68	0.939
C15	0.56	0.561	0.34	0.342	0.39	0.463
C16	0.45	0.460	0.38	0.342	0.38	0.671
C17	0.31	0.303	0.28	0.389	0.28	0.374
C18	0.24	0.237	0.29	0.277	0.29	0.389
C19	0.45	0.441	0.47	0.286	0.34	0.277

8 | Conclusion

In conclusion, this paper introduces an innovative approach for evaluating and predicting the risks associated with renewable power plant construction, employing an integrated method that combines DEA and SVM. Our proposed methodology addresses the shortcomings of traditional RPN assessments, offering a more robust and nuanced framework for risk evaluation and efficiency prediction based on risk information. Applying DEA cross-efficiency as an alternative to RPN values demonstrates the latter's limitations, emphasizing the need for a more reliable risk assessment method. The findings highlight that the risk factor with the highest associated risk is "Low Productiveness for Solar Power Plant Construction," as determined by DEA scores. Furthermore, the SVM approach proves essential in predicting risk factor scores, particularly crucial in scenarios where improvements to one factor could impact others. Our comprehensive evaluation, focusing on 19 selected failure modes in constructing renewable energy power plants, provides valuable insights into each mode's varying degrees of risk. The results indicate disparities between the prioritization outcomes based on DEA scores and RPN values, confirming that the traditional RPN index may not be the most effective tool for risk prioritization.

This study contributes to advancing risk assessment methodologies in the renewable energy sector, offering a more accurate and reliable means of evaluating and predicting risks. The proposed integrated approach holds promise for practical applications in guiding decision-making processes and risk management strategies in constructing renewable power plants. Further research and application of this methodology could yield even more refined insights and contribute to enhancing risk assessment practices in the renewable energy industry.

8.1 | Future Research Suggestions

The future research suggestions include expanding the scope by integrating additional risk factors, conducting comparative analyses with established risk assessment models, applying the proposed methodology to real-world case studies, exploring dynamic risk assessment, incorporating environmental and social factors, optimizing the machine learning model, validating and benchmarking against industry standards, involving stakeholders in model development, assessing long-term performance, and adapting the approach to different renewable technologies. These recommendations aim to enhance the applicability, robustness, and real-world impact of the proposed risk assessment methodology in constructing renewable power plants.

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