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ORIGINAL

Enhancing industrial decision-making through Multi-Criteria Decision-Making approaches and ML-Integrated Frameworks

Mejorando la toma de decisiones industriales a través de enfoques de toma de decisiones multicriterio y marcos integrados con aprendizaje automático

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ABSTRACT

Decision-making in current industrial contexts has shifted from intuition to a data-driven approach, requiring prompt processing of huge datasets. However, conventional Multi-Criteria Decision Making (MCDM) methodologies fall short of navigating the intricacy of large datasets. This paper introduces an innovative decision-support system integrating multi-criteria methods with machine learning techniques such as artificial neural networks. The proposed six-step framework aims to optimize operational decisions by analyzing real-time performance data. The research contributes to the advancement of decision-making methodologies in the industrial field, offering dynamic responsiveness and improved recommendations compared to traditional MCDM methods. While results are promising, future work should focus on robustness testing particularly in terms of its dependence on real-time data, to ensure sustained efficacy and mitigate potential biases in recommendations over time.

Keywords: Decision making, Industrial real-time performance, Multi-Criteria Decision Making, AHP, Artificial Neural Network.

RESUMEN

La toma de decisiones en los contextos industriales actuales ha pasado de ser intuitiva a un enfoque basado en datos, lo que requiere el procesamiento rápido de grandes conjuntos de datos. Sin embargo, las metodologías convencionales de Toma de Decisiones Multicriterio (MCDM) no logran manejar la complejidad de grandes conjuntos de datos. Este artículo presenta un sistema innovador de soporte a la decisión que integra métodos multicriterio con técnicas de aprendizaje automático, como redes neuronales artificiales. El marco propuesto de seis pasos tiene como objetivo optimizar las decisiones operativas mediante el análisis de datos de rendimiento en tiempo real. La investigación contribuye al avance de las metodologías de toma de decisiones en el campo industrial, ofreciendo una capacidad de respuesta dinámica y recomendaciones mejoradas en comparación con los métodos MCDM tradicionales. Aunque los resultados son prometedores, el trabajo futuro debe centrarse en la prueba de robustez, particularmente en términos de su dependencia de los datos en tiempo real, para asegurar una eficacia sostenida y mitigar posibles sesgos en las recomendaciones a lo largo del tiempo.

Palabras clave: Toma de decisiones, rendimiento industrial en tiempo real, Toma de Decisiones Multicriterio, AHP, Red Neuronal Artificial.

INTRODUCTION

Decision-making in industrial settings has undergone a notable transformation, transitioning from intuitive judgment relying on experience to a data-driven approach in the information era leveraging data to gain insights into customers' needs and preferences as well as market conditions to inform decisions, leading continuous improvement of process to enhance operational efficiency, and ultimately boost profitability. Literature reveals a wide range of multi-criteria decision-making methods used for data-driven industrial decision-making problem-solving. The process is complex and involves multiple steps, including identifying a business problem, seeking information about different possible decisions, evaluating the alternatives based on the gathered information culminating in the selection, implementing the decision in business operations, and monitoring the situation to make adjustments if needed.(1)

Meanwhile, the ability of conventional MCDMs to deliver effective decisions that stem from a comprehensive evaluation of alternatives is compromised by their inability to handle large datasets associated with several factors that characterize modern industrial operations, especially since modern processes are designed to be data centered endowing capabilities for the creation and utilization of large datasets (big data) thus rendering them rule-based and case-oriented.(2)

Therefore, industrials are challenged to explore machine learning frameworks to transform disparate data into actionable intelligence for optimal decision-making.(3) The effectiveness of decision-making relies on the efficient integration of analytical models and data. The appropriate modeling enhances decision-making outcomes while the velocity and accuracy with which information is collected, along with the usage of intelligent data, add to the quality of the decision.(4)

Recognizing the growing need for self-sufficient and accurate decisional intelligence, the present search introduces an innovative hybrid technique combining optimal multi-criteria decision-making methodologies with machine learning algorithms for discovering and earning patterns in massive datasets to assist decision-makers in making optimum operational decisions while taking into account real-time industrial performance data.

This paper is structured around five sections, in the first section, a literature review is presented while emphasizing the paper's contribution and novelty. Section II introduces the methodology, Section III details the construction of the decision-support system, Section IV presents the results, and Section V covers a case study. Finally, the findings are summarized in Section VI, with suggestions for future research.

Related work

This section offers a concise overview of the distinctive facets of industrial decision-making within the framework of Industry 4.0. A comprehensive literature review is conducted, focusing on prevalent decision-making methods, while also emphasizing the diverse contributions of machine learning in optimizing industrial processes.

The intersection of data analytics and Industry 4.0 is a rapidly growing subject of research, focusing on data's critical role in improving operations and enabling intelligent decision-making. Intelligent production systems in Industry 4.0 require data-driven techniques, particularly for condition monitoring.(5,6) it is also a requirement for Industry 4.0 maturity considering that it enables real-time incident reaction and data-driven decision-making, both of which are critical for organization agility.(7) Hence data analysis is increasingly becoming at the heart of all industrial operations, notably decision-making.

Industrial performance problems are often complicated and multidimensional, with a vast array of possible variables influencing output outcomes.(8) To conquer their complexity Multi-criteria decision-making (MCDM) methods are widely employed as they involve several optimization parameters. MCDM methods offer a systematic approach that considers several factors from various fields and allows the assessment of decisions with disproportionate and contradicting consequences, facilitating effective decision-making procedures. These methods serve as a key for increasing the involvement of stakeholders and instilling trust in decision-making by allowing pair-wise comparison of alternatives.(9) In particular, the weighted sum approach remains fundamental in MCDM problems.(10)

Decades of accumulated data-driven statistics unveil that the Analytic Hierarchy Process (AHP) stands as the most widely adopted approach mainly because of the algorithm's simplicity and effectiveness as well as its unique ability to capture and incorporate users' perceptions effectively, particularly when addressing intricate and multifaceted problems while identifying and minimizing inconsistencies in opinions.(11,12,13) AHP offers a structured three-step process centered around numerical values through pair-wise comparisons.(14) The first step involves the construction of a hierarchical structure, where the performance goal assumes the top-level position, criteria are placed at the second level, and alternatives are delineated at the third level. In Step 2, the relative importance of decision-making criteria is determined by quantifying their significance associated with achieving the goal using Saaty's scale of relative importance and assessed via pair-wise comparison. The final step involves assessing the consistency of the pair-wise comparison matrix to before proceeding with further analysis. The consistency ratio is calculated by dividing the Consistency Index (CI) derived from the largest eigenvalue (λmax) by the Random index.

$$CR = \frac{CI}{RI};\ CI = \frac{\lambda_{max} - n}{n-1}$$

Depending on the calculated Consistency Ratio (CR) value, different scenarios are distinguished.

- CR < 0,1, the pair-wise comparisons are considered acceptable, with a satisfactory level of consistency.
- CR > 0,1, the pair-wise comparisons are deemed inconsistent and require reevaluation.
- CR=0 perfect pair-wise comparisons.[15,16]

Table 1. Saaty's relative importance scale

Importance value	Interpretation
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values

The rise of Industry 4.0 has resulted in a substantial influx of real-time data from the factory floor, challenging thus the efficacy of conventional multi-criteria decision-making methods. Their incapacity to handle extensive data volumes undermines their effectiveness. Additionally, their temporal independence fails to align with the dynamic nature of industrial performance. These limitations create an opportunity to incorporate machine learning in business processes to capitalize on this data to enhance decision-making processes in Industry 4.0 with applications covering a wide range of industrial challenges such as production planning, control, and defect analysis highlighting how machine-learning approaches may contribute to improvements in predictive modeling and decision-making and revolutionize efficiency.[17] Machine Learning is transforming decision-making in various industries, making them more capable of handling complicated patterns by fine-tuning computational abilities through experiential learning and using the power of online data and cost-effective computing.[18,19]

Supervised machine learning is widely used in industrial research due to its superior performance over unsupervised learning.[20] A common and valuable supervised learning system in predictive analytics is Random forests (RF). RF performs in regression and classification problems and is recognized for its high predicted accuracy. The algorithm creates decision tree ensembles on randomly selected data subspaces to reduce overfitting and improve generalization producing robust models that successfully capture complicated patterns.[21,22] Another straightforward yet powerful machine learning approach that is extensively used in various applications, including industrial decision-making is the K-Nearest Neighbor (KNN). The KNN is remarkable for its non-parametric character since it makes predictions or classifications based on the proximity of data points. Its simplicity, along with reasonably strong accuracy across a variety of situations, has positioned KNN as a preferred alternative amongst other machine learning techniques.[23,24,25,26] Furthermore, the literature has various industrial applications incorporating artificial neural networks (ANNs), indicating their extensive potential for fast and effective data analytics while presenting results in an intelligible format for users.[27] Research also suggests that ANNs can improve process management and control systems, although their effectiveness varies based on the situation at hand.[28] Artificial intelligence, especially machine learning, according to Meddaoui et al. is is widely used in industry, particularly in the field of machine learning to predict future data based on inputs and KPIs. These researchers have shown that ANN (Artificial Neural Networks) is extensively used in industrial maintenance to predict failures.[29]

The current work extends previous research by presenting an innovative approach to decision support systems that leverages the capabilities of machine learning algorithms and the structured decision-making approach of AHP, to offer a robust and responsive framework for enhancing decision support in dynamic environments, that overcomes the aforementioned limits of conventional decision-making frameworks particularly in the context of Industry 4.0 and its demand for agile and data-driven decision-making.

METHOD

The proposed decision-support system is structured around a six-step decision-making methodology, which is divided into two main blocks. The first block involves the establishment of a well-defined decision-making framework. The process initiates with a clear definition of the company's vision and performance objectives. Indicators are then assigned to these objectives, and a prioritization is conducted to better align with the decision-making strategy. The second block of the process commences with the identification of alternatives. Subsequently, a scoring mechanism is applied to these alternatives, and the final step involves evaluating the alternatives to select the optimal one. This comprehensive methodology ensures a systematic approach to decision-making, integrating both strategic vision and performance objectives (figure 1).

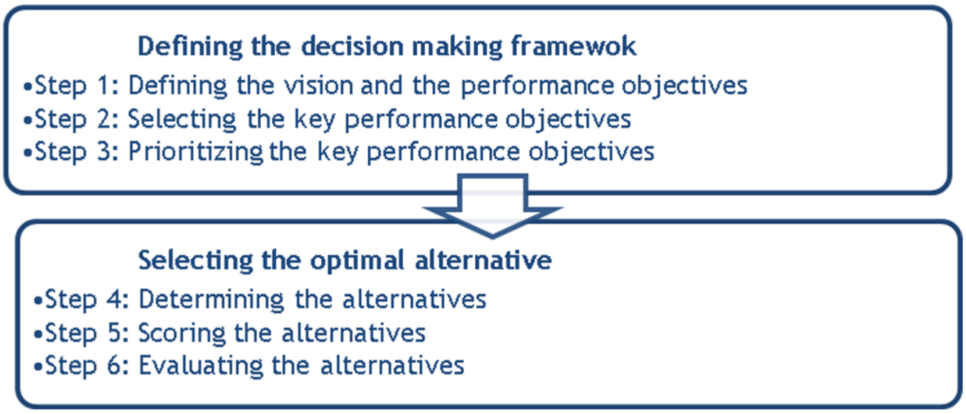

Figure 1. Decision-making methodology

Defining the decision-making framework

To better assist industrial decision-making, the model has been built to be fully adaptable to the specifics that distinguish each organization. thereby, the implementation entails the establishment of a tailored performance measurement system, considering that the effectiveness of the decision-making relies upon supplying valuable inputs that can only be drawn from a holistic performance measurement system that reflects an accurate overall view of the business's current state from four key perspectives. This approach ensures that all critical aspects are simultaneously evaluated and detects sub-optimal decisions where improvements in one aspect might negatively impact another, rather than concentrating solely on financial metrics. This prevents the suboptimization often seen with traditional systems which can be detrimental to the overall performance.

Step 1: defining the vision and performance objectives

During this stage, managers are interviewed to clarify the organization's vision and create an initial list of objectives across the four performance perspectives outlined by the balanced scorecard method: financial, customer, internal business, and innovation and learning. This process involves addressing the following key questions:

- To succeed financially, how should the organization appear to its shareholders?
- To achieve this vision, how should the organization appear to its customers?
- To satisfy its shareholders and customers what business process must be excelled at?
- To achieve this vision, how will the organization sustain its ability to change and improve?

Step 2: determining the key performance objectives

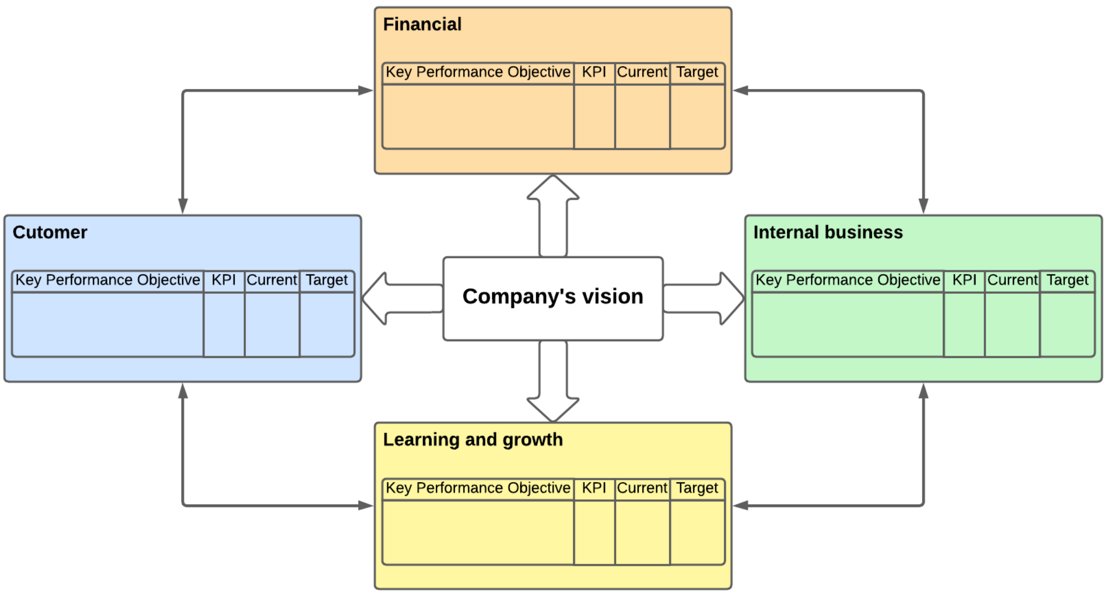

Figure 2. Balanced scorecard with KPIs

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Figure 2 shows the global operators of the company's vision. Performance indicators are developed with executives and objectives are shortlisted to less than 20 measurable objectives focusing only on necessary and sufficient metrics. Each objective is assigned a key performance indicator (KPI) with a current and target performance value to help the decision-maker get a clear understanding of how the company has been performing and its future direction, ensuring that both the strategic and operational levels are operating simultaneously and their efforts are driving towards the same goal.(30,31) Before moving forward, a review session is conducted with managers and executives to verify that the BSC translates accurately to the overall strategy they are striving for.

Step 3: Prioritizing key performance objectives

To ensure that the most important aspects of the organization's strategy are given the appropriate attention and resources drawing on the data acquired through the balanced scorecard analysis, decision-makers are tasked to conduct a Hierarchical Process Analysis (AHP) to ascertain the relative importance of the key performance objectives retained from the prior stage and weights them accordingly (figure 3).

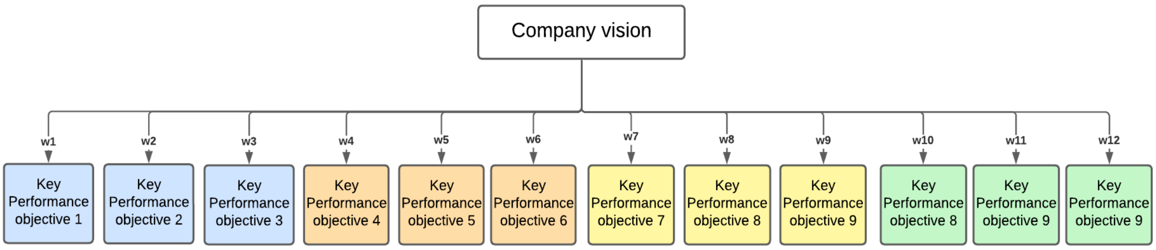

Figure 3. Decision-making hierarchy

To perform AHP, we follow these steps:

- Define the problem and its components: the hierarchical structure is mapped out with the company vision at the highest level followed by key performance objectives at the second level.
- Create a pairwise comparison matrix: managers are required with the support of executives to determine the relative importance of different performance criteria with respect to the overall goal using the help of Saaty's scale of relative importance, with 1 indicating equal importance and 9 indicating that one performance objective is much more important than the other.
- Calculate the priority vector: the pair-wise comparison matrix is subsequently normalized to derive a priority vector that incorporates the respective weights assigned to performance objectives.
- Perform consistency checks: consistency ratio is calculated and if it falls outside the designated threshold pair-wise comparisons are revisited for reassessment.

The outcomes of these two stages can be utilized to formulate the objective function, representing the overall performance of the company expressed as the weighted sum of sub-performances, each associated with its respective performance objective.

$$P(t) = \sum_{i=1}^{n} w_i . p_i(t)$$

Where:

- p_i: The company's performance against the objective i.
- w_i: Contribution of the objective i to the overall performance.
- n: Number of objectives defined.

Selecting the optimal alternative

Step 4: determination alternatives

This step is performed anytime a problem emerges. The decision-making panel should include interdisciplinary decision-makers to ensure a comprehensive understanding of the problem at hand from multiple perspectives. Their role is to brainstorm and generate a list of all possible solutions, even unconventional ones. To promote creativity and innovation, varied brainstorming approaches such as reverse brainstorming, mind mapping, word association, role-playing, and group brainstorming might be employed. The alternatives are compiled into a list after removing duplicates for reference in the following phases of the decision-making process.

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Step 5: scoring alternatives

The ultimate objective in optimizing a company's overall performance is to identify the alternative that maximizes the overall performance. Although alternatives are not expressly included in the objective function, their influence directly affects the overall performance. To overcome this challenge, the approach employs a scoring principle derived from the AHP method to quantify the impact of each alternative. Executives are required to score each alternative's potential contribution to each specific performance objective with the help of the rating system illustrated in table 2.

Table 2. Relative importance scale

Importance value	Interpretation
1	Negative to no contribution to the specific performance objective
3	Little to no positive contribution to the specific performance objective
5	Moderate positive contribution to the specific performance objective
7	Very strong positive contribution to the specific performance objective
9	Extreme positive contribution to the specific performance objective
2,4,6,8	Intermediate values

Step 6: alternatives evaluation

Alternative evaluation in industrial decision-making differs from other multi-criteria decision-making situations is that the impact of an alternative is not a static attribute; rather, it varies in real-time based variations in performance levels. However, Traditional Multiple Criteria Decision-Making (MCDM) approaches presume a static process, focusing primarily on the possible impact of alternatives on performance objectives, and fail to account for the ever-changing dynamics of industrial performance. Recognizing this limitation, the suggested alternative scoring approach provides a dynamic framework based on the potential impact of alternatives on performance goals, based on the judgment of the decision-maker adjusted according to the current performance using the equation below. This approach makes the model responsive and dynamic, enabling more accurate and contextually relevant decision-making, resulting in a more flexible and context-aware decision-making approach better suited for industrial decision-making.

$$S = \sum_{i=1}^{n} w_i . s_i . (1 + g_j)$$

Where:

- s_i: Score of the alternative against the objective i.
- w_i: Contribution of the objective i to the overall performance.
- g_j: Performance gap between current and target performance against objective i.
- n: Number of objectives defined.

DEVELOPMENT

To alleviate the cognitive burden associated with the industrial decision-making process, the proposed decision-making approach is further enhanced by leveraging machine learning algorithms. The artificial intelligence module will serve as the decision-making brain as shown in figure 4. It will receive as input the target performance values per objective, and the scores assigned to the alternatives by the decision-makers against each of the objectives, as well as the real performance values to return the alternatives classified according to their overall score. The incorporation of these advanced techniques will not only streamline the decision-making process but also improve its efficacy, making it more responsive to complex and dynamic scenarios.

To determine the optimal architecture of our decision-support system, we followed a two-step process. First, we identified the most suitable machine learning algorithm by comparing the performance of three different algorithms, ultimately selecting the one that performed best for our specific case. The second step involved optimizing the model's structure through a trial-and-error approach, refining the architecture to enhance overall system performance.

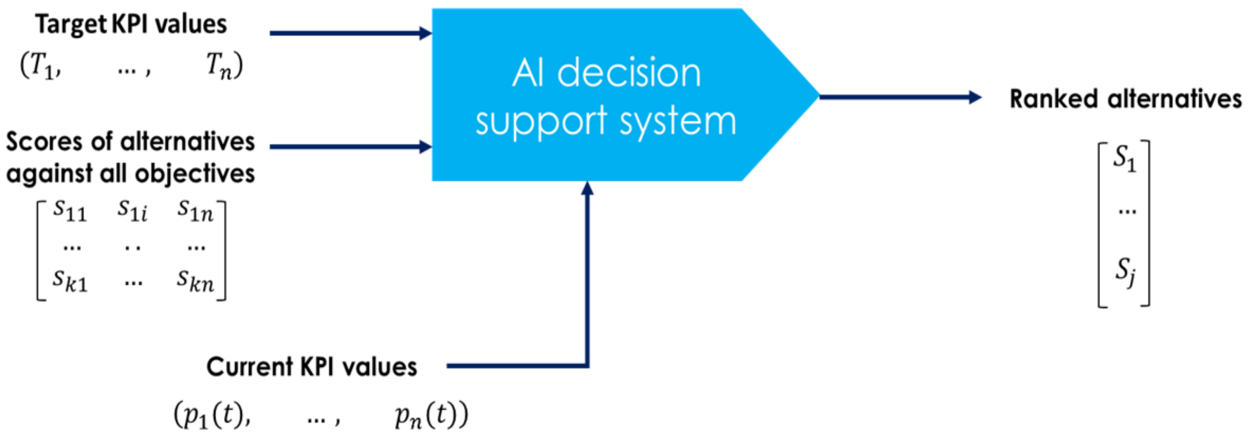

Figure 4. Decision-support system modeling

Selecting the machine learning framework

In the context of industrial performance, supervised machine learning is commonly employed.[32] Based on the decision-making framework previously outlined, the decision-making problem aligns with a prediction problem. As such, K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Random Forest (RF) were explored using Orange a powerful data mining software to determine the most relevant one for solving the specific problem on hand. Orange is a robust, open-source machine learning and data visualization suite that provides a comprehensive visualization-driven environment for data science.

To construct the evaluation database, we focused on the scenario of a small enterprise with 12 performance indicators distributed across four perspectives: financial, customer, internal business, and innovation. Experts across different performance contexts carefully defined and subsequently evaluated the alternatives. The resulting dataset comprises 500 entries, where each entry represents a unique combination of performance indicators and expert evaluations. The dataset was systematically partitioned into an 80 % training set and 20 % test set and used to train all 4 machine learning methods in parallel. The efficiency of the methods in capturing and learning features was evaluated using: Mean Square Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), as well as the Coefficient of Determination (R^2). The results of these evaluations are presented in table 3.

Table 3. Training results and accuracy of the compared algorithms

ML-algorithm	MSE	RMSE	MAE	MAPE	R^2
K-nearest neighbor	0,304	0,551	0,446	0,078	0,732
Artificial neural network	0,023	0,153	0,120	0,022	0,979
Random Forest	0,303	0,551	0,440	0,077	0,733

The K-Nearest Neighbors (KNN) approach has modest performance across metrics and a decent R^2 value, suggesting an acceptable capacity to learn data patterns. The Random Forest approach is competitive, providing results similar to KNN across all metrics. The Artificial Neural Network (ANN) on the other hand performed well, with low errors across all metrics and a high R^2 value, indicating an excellent ability to identify and predict data patterns making it an ideal option for predictive modeling in the case at hand.

Optimizing the model's architecture

The input and output layers of our ANN are already defined as the system takes as input the scores of the alternative per performance objective (at a number of 12 in our case) and the average of performance per objective (at the number of 12 in our case) and return a single value which is the alternative overall score Thus the input Layer shall contain 24 neurons and output layers has 1 single neuron, next, we will be looking at the number of hidden layers and neurons per each layer (figure 5).

The number of hidden neurons is an essential parameter that influences the performance of the ANN. It is important to avoid using too few hidden neurons, resulting in underfitting, or too many, causing an overfitting. Although there is no uniform approach for determining the ideal ANN design, various guidelines are used to identify the appropriate number of neurons in hidden layers. In general, the number of hidden layers depends on the function the ANN will be serving, when the ANN is designed to be capable of representing linear separable functions or decisions no hidden layer is needed, when it's intended to approximate any function that contains a continuous mapping from one finite space to another we should be looking at a single hidden layer when it's expected to represent a random decision boundary to a random accuracy with rational activation functions and approximate any smooth mapping to any accuracy two hidden layers are needed.

Since our system needs to estimate a global score of an alternative based on an elementary score per performance objective and current performance that can be best assimilated to a function that contains a continuous mapping from one finite space to another, we will need a single hidden layer. The number of hidden neurons should ideally lie within the size of the layer that inputs data and the size of the output layer, and it must also be beneath two times the dimensions of the input layer. Therefore, the optimal structure of the ANN in our context comprises a single hidden layer containing between 2 and 14 neurons. The optimal configuration is determined via a trial-and-error process.

Table 4. Mean square error results for different hidden layer configurations

Number of hidden neurons	Mean Square Error (MSE)
2 hidden neurons	7,40E-04
3 hidden neurons	2,12E-07
4 hidden neurons	4,77E-04
5 hidden neurons	5,82E-04
6 hidden neurons	5,76E-04
7 hidden neurons	2,30E-03
8 hidden neurons	1,30E-03
10 hidden neurons	1,7 E-03
12 hidden neurons	2,20E-03
14 hidden neurons	1,90E-03

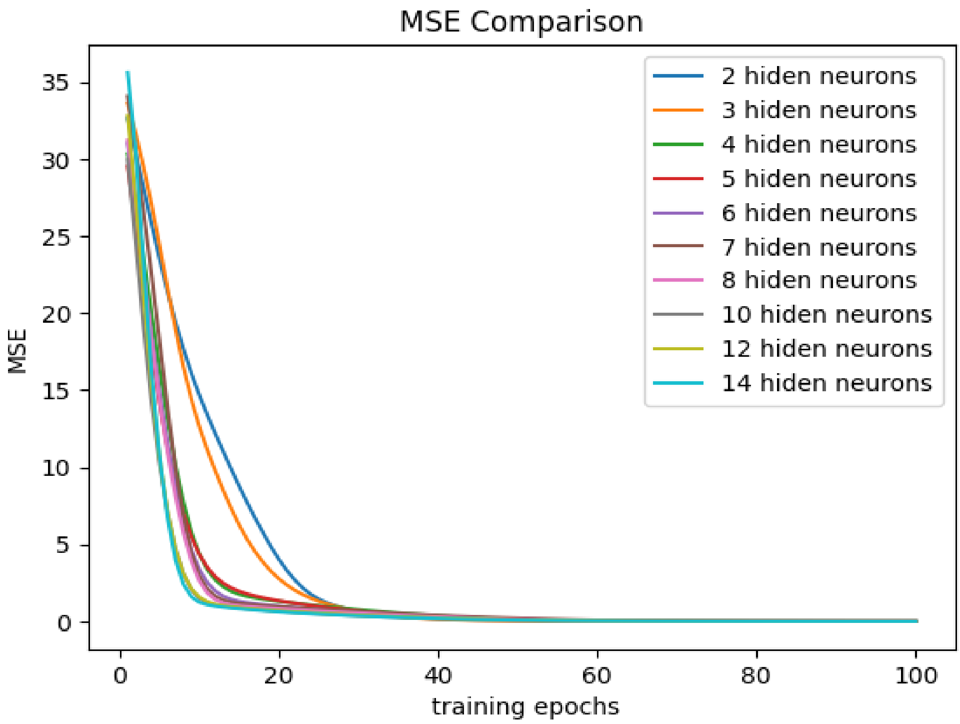

Figure 5. Training results for different hidden layer configurations

As shown in table 4 and figure 6, the optimal structure was determined to include 24 input neurons, 3 hidden neurons, and 1 output neuron as experimentation revealed that the lowest MSE level, at 2,12E-07, was attained with a hidden layer comprising 3 neurons.

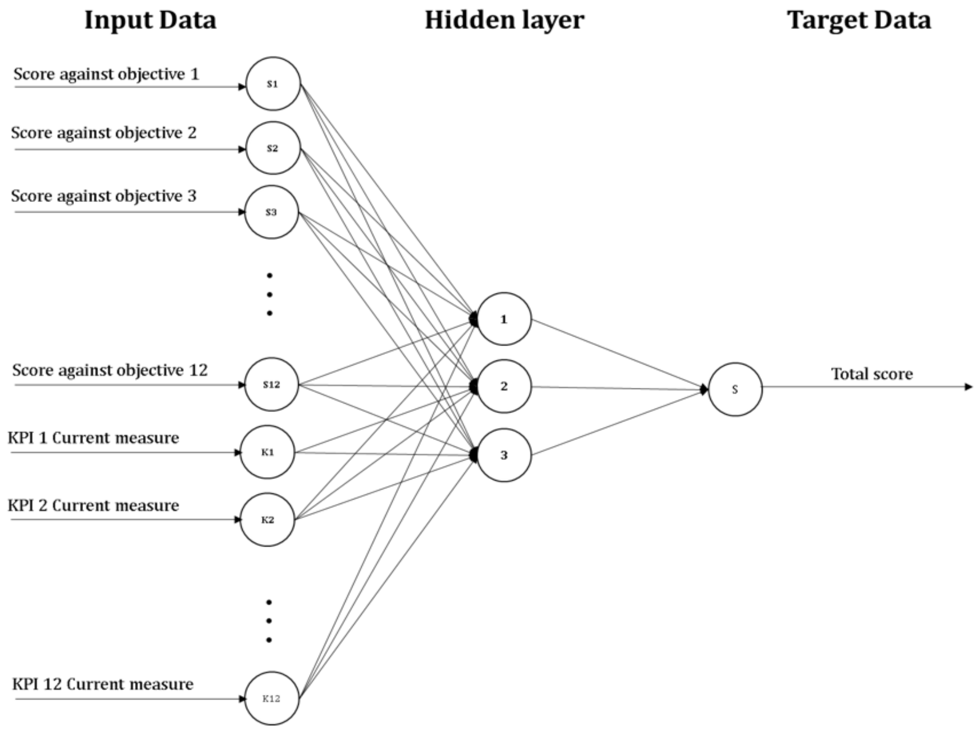

Figure 6. The optimized neural network structure

RESULTS

In order to evaluate the performance of our predictive model, we conducted a comprehensive comparison between the predicted values generated by the model and the actual observed values. This comparison is visualized on a scatter plot in the figure 7, which specifically highlights the first 30 data points where the actual values are depicted in red, and the predicted values in blue.

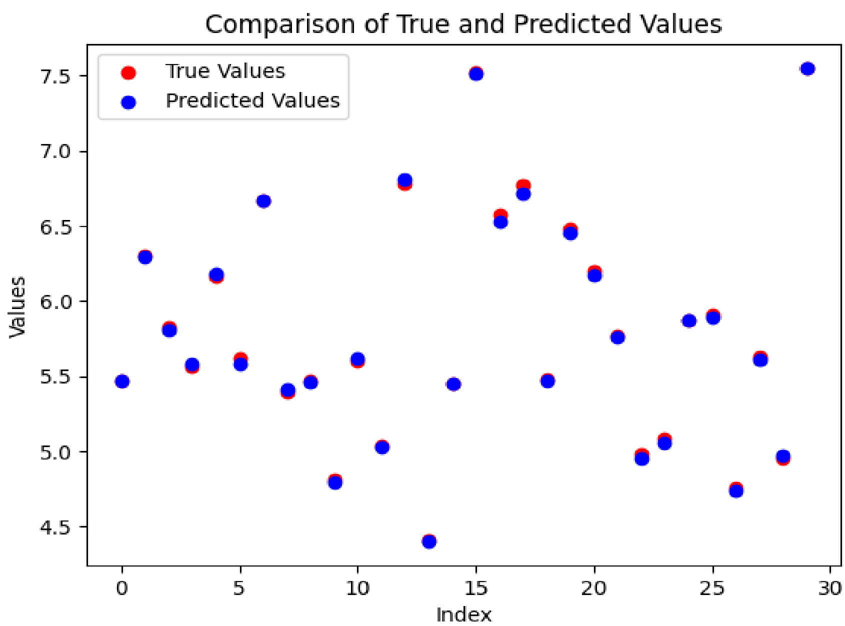

Figure 7. Comparison of predicted and true values

As illustrated, the red and blue points frequently converge, with many instances where the points are so closely aligned that they overlap entirely. This overlapping of points serves as a clear visual indication of the model's high level of accuracy. The proximity of the predicted values (in blue) to the actual values (in red) suggests that the model consistently produces predictions that are nearly indistinguishable from the true data. This strong alignment between the two sets of values highlights the model's robustness and its ability to reliably capture and reflect the underlying patterns within the dataset. Such performance is crucial in ensuring that the decision-support system can provide trustworthy and precise outputs, which are essential for informed decision-making in real-world applications

Case study: model validation

To validate the model and assess its capability to leverage real performance data we implement it in an industrial setting and conduct a comparative analysis of the outputs. We compare the results generated by the model with those obtained from the Analytic Hierarchy Process (AHP) in two distinct scenarios characterized by different performance values. This comparison serves as a rigorous test, evaluating the model's performance across varying performance conditions and providing insights into its effectiveness in practical, real-world situations.

Defining the decision-making problem

The model is used to help the company decide on the optimal course of action to take to face the problem of the increase in customer complaints a small-sized company operating in the automotive sector has been experiencing recently due to product defects and quality issues to improve quality and reduce defects to maintain customer satisfaction and competitiveness and improve company's overall industrial performance.

The company has four alternatives to choose from:

- Alternative 1 (A1): Invest in Advanced Quality Control Systems: this involves implementing state-of-the-art quality control technologies and equipment to detect defects early in the production process.
- Alternative 2 (A2): Implement Robust Training Programs: Focus on enhancing employee skills and training to ensure proper assembly and testing procedures, leading to fewer defects.
- Alternative 3 (A3) Enhance Supplier Quality Management: Strengthen collaboration with suppliers, set stringent quality standards, and conduct regular audits to ensure the supply of high-quality components.
- Alternative 4 (A4) Redesign Critical Production Processes: Identify and redesign problematic production steps to eliminate root causes of defects.

Phase I: Defining the decision-making framework

As mentioned in table 5, company managers and experts were asked to work together to lay out the vision of a small-sized firm that operates within the automobile manufacturing industry, which we consider to be an application case for our decision-making approach, Interviews and multiple barnstorming sessions conducted with the management team allowed us to define their vision and strategy and break it down into performance objectives, which were assessed with the help of the executives and reduced to 12 measurable objectives distributed over four perspectives: financial, customer, internal business, and innovation and learning reflecting the company's vision taking into account the company's potential (means and resources) as well as market trends and challenges.

The next stage involves capturing the "As is situation" and setting performance targets to achieve the "To be situation". The goal is to continuously challenge the company's processes using the kaizen principle to achieve the outlined vision.

Table 5. Balanced scorecard of the studied company operating in the automotive field

Strategic objective		Performance measure		
		Key performance indicator	**As-is situation**	**To-be situation**
Financial	Obj1. Increase profit	Net profit margin	10 %	25 %
	Obj2. Make profitable investments	ROI (Return on Investment)	15 %	50 %
	Obj3. Increase sales	Revenue growth rate	5 %	20 %
customer	Obj4. Satisfy customers	Complaint's rate	30 %	5 %
	Obj5. Increase market share	Market share index	5 %	20 %
	Obj6. Retain customers	Customer retention rate	70 %	90 %
internal process	Obj7. Increase availability	Operational availability rate	79 %	98 %
	Obj8. Have efficient processes	Performance rate	85 %	95 %
	Obj9. Produce high-quality products	Quality rate	80 %	98 %
learning and growth	Obj10. Have a well-trained staff	Job role competency rate	75 %	
	Obj11. Retain employees	Employee turnover	9 %	
	Obj12. Engage employees	Employee participation rate	6 %	

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To complete the decisional framework, a pairwise comparison of Key performance objectives was done in multiple iterations with the participation of managers to prioritize KPOs and determine their respective weights until the evaluation of the consistency ratio was validated with a CR = 0,1 falling inside the threshold (figure 8).

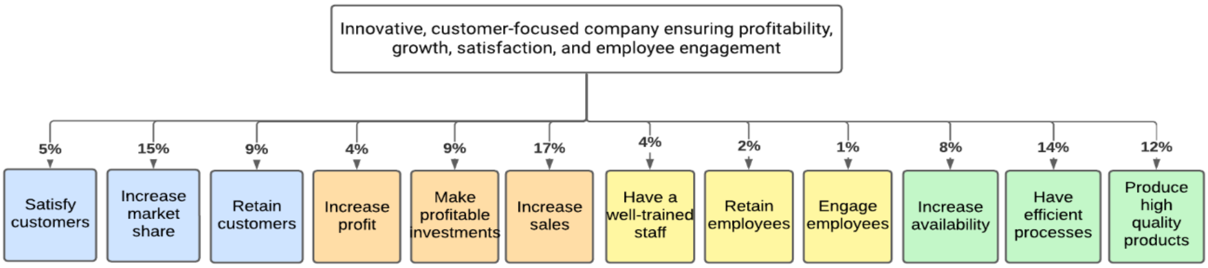

Figure 8. The Decision-making hierarchy of a company operating in the automotive sector

Phase II: Selecting the optimal alternative

Decision-makers are required to detail each of the alternatives according to the effect it could have on each of the performance objectives in order to assign a score using a structured and uniform assessment scale ranging from 1 to 9 providing a comprehensive range of scores 1,3,5,7 but also introduces intermediate values to accommodate nuanced assessments offering a systematic and transparent means of gauging the potential impact of alternatives on our specified performance objectives.

For example, investing in advanced quality control systems has an initially neutral to negative impact on net profit margin due to upfront costs which will be positive over time when the solution turns out to be efficient as cost savings are realized.

1. The impact on the net profit is neutral initially, potentially turning positive as benefits accrue.
2. The impact on the return on investment is neutral initially, potentially turning positive as cost savings are realized.
3. The impact on revenue is positive with increased customer satisfaction and loyalty by enhancing goods quality
4. The impact on complaints rate is positive as the system identifies and addresses quality issues
5. The impact on the market share is positive depending on the improvement in complaints rate and product quality
6. The impact on customer retention is positive as high-quality products contribute to improved customer satisfaction
7. The impact on operational availability is neutral to positive by reducing the quality issues requiring production suspension decreasing the operational availability
8. Impact on performance rate is neutral to positive particularly if the system targets specific areas affecting performance
9. Impact on the quality rate is positive, as the system detects and rectifies defects or deviations
10. The impact on job Role Competency Rate is positive, as employees adapt to and gain proficiency in using the new system.
11. The impact on employee turnover is neutral to positive, depending on the system's effect on job satisfaction and stress reduction.
12. The impact on Employee Participation Rate is neutral to positive

Similarly, the other alternatives undergo an evaluation to ascertain their elementary scores, which are then summarized in table 5.

Table 6. Alternatives scoring

	KPO1	KPO2	KPO3	KPO4	KPO5	KPO6	KPO7	KPO8	KPO9	KPO10	KPO11	KPO12
A1	2,00	2,00	4,00	7,00	5,00	7,00	2,00	7,00	9,00	5,00	2,00	2,00
A2	2,00	2,00	4,00	5,00	4,00	3,00	2,00	5,00	7,00	9,00	9,00	9,00
A3	2,00	2,00	4,00	4,00	5,00	3,00	3,00	4,00	5,00	2,00	2,00	2,00
A4	1,00	1,00	5,00	7,00	5,00	5,00	7,00	7,00	7,00	2,00	2,00	7,00

Results for industrial performance scenario #1

We use the developed intelligent decision-support system and the conventional AHP method to determine the best strategy to follow at a given point in time characterized by the industrial performance figure 9.

https://doi.org/10.56294/dm2024.391

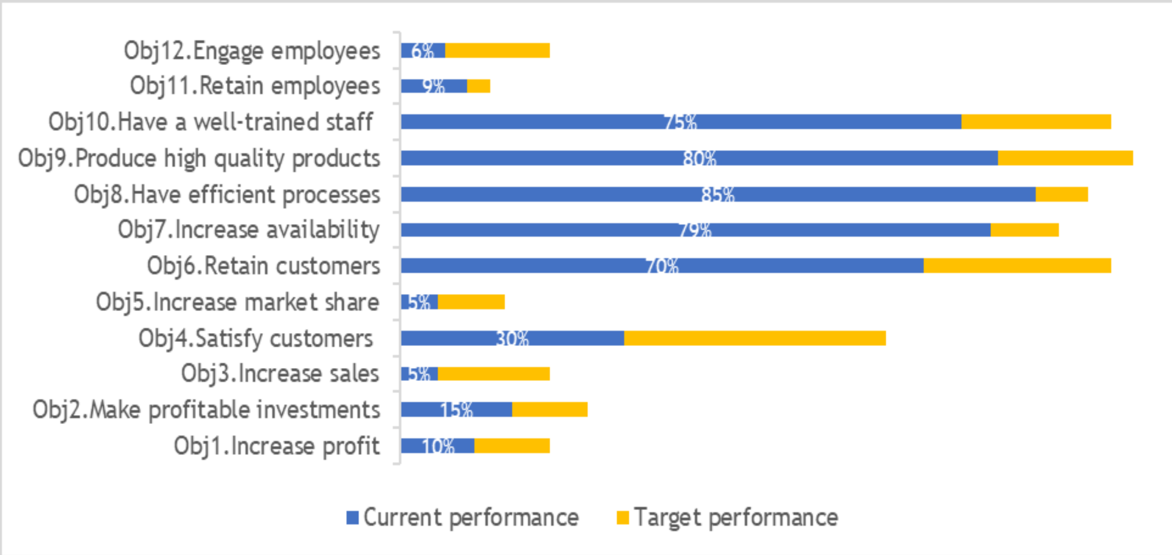

Figure 9. Real-time industrial performance for scenario #1

Table 7. Alternatives ranking for the first performance case		
Alternatives	**ANN model**	**AHP**
A4. Redesign Critical Production Processes	14,10	5,11
A1. Invest in Advanced Quality Control Systems	13,68	5,20
A2. Implement Robust Training Programs	13,24	4,16
A3. Enhance Supplier Quality Management	10,34	3,70

As mentioned in table 5 related to case 1, the ANN model yields a different ranking compared to the AHP. ANN model suggests prioritizing "A4-Redesign Critical Production Processes" (bold line) first, followed by "A1-Invest in Advanced Quality Control Systems," then A2 and A3. This disparity in rankings between the two models indicates variations in their assessments based on the specific performance values in the given scenario.

Results for industrial performance scenario #2

We replicate the same exercise at a different point in time characterized by the industrial performance illustrated in figure 10 and compare the results of conventional AHP and the developed model.

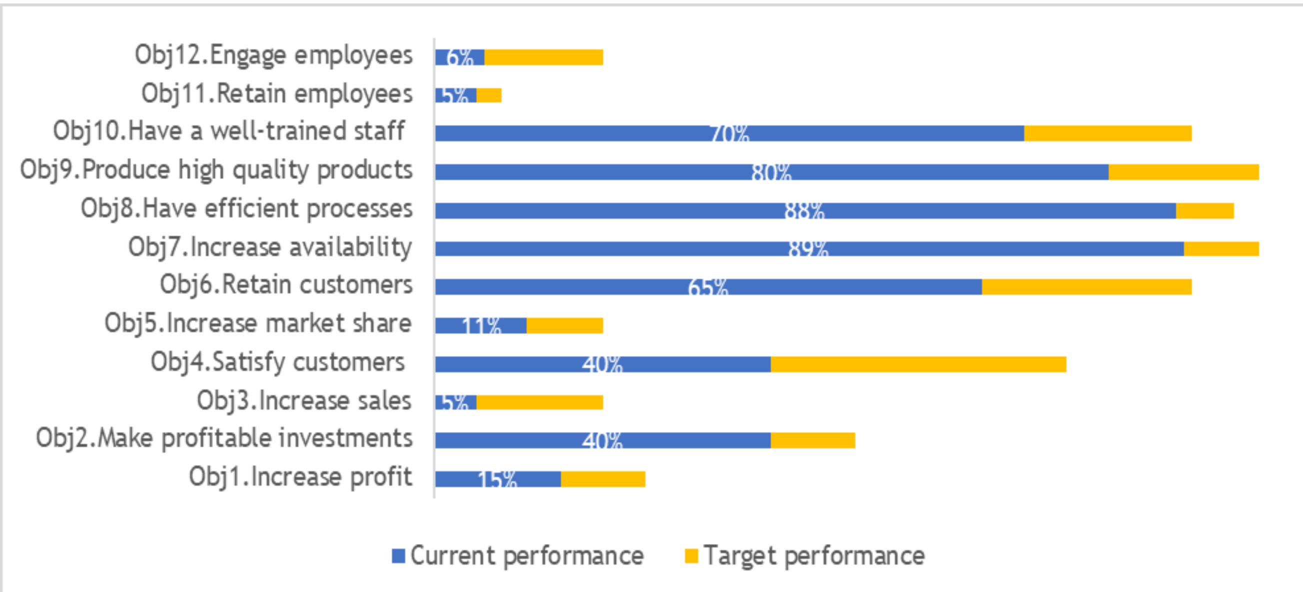

Figure 10. Real-time industrial performance for scenario #1

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Table 8. Alternatives ranking for the second performance case		
Alternative	**ANN model**	**AHP**
A1. Invest in Advanced Quality Control Systems	13,08	5,20
A4. Redesign Critical Production Processes	12,86	5,11
A2. Implement Robust Training Programs	11,99	4,16
A3. Enhance Supplier Quality Management	9,19	3,70

In this second case, both the ANN model and AHP approach provide identical classifications of the alternatives, prioritizing them as follows: "A1-Invest in Advanced Quality Control Systems," followed by "A4-Redesign Critical Production Processes," then A2 and A3.

The divergent rankings between the two cases reflect distinct strategic priorities. In the second ranking, the emphasis is placed on immediate investment to address quality issues and improve customer satisfaction, aiming to reduce complaints and enhance overall product quality. This reflects a proactive approach prioritizing direct investment for quality improvement. In contrast, the first ranking employs redesign of problematic production processes to address indicating a strategic consideration of cost-effectiveness and resource allocation, focusing on resolving quality issues with limited financial resources.

CONCLUSION

In conclusion, the developed model represents a significant advancement in decision-making methodologies within industrial contexts. Delivering pertinent recommendations based on real-time performance indicators, it demonstrates a level of dynamic responsiveness that distinguishes it from conventional Multiple Criteria Decision-Making methods. The integration of Machine Learning into the industrial decision-making process not only enhances the efficiency of decision-making but also opens up new horizons for the development of hybrid methodologies. However, the robustness of the model must be rigorously tested, particularly regarding its dependency on real-time data. This critical evaluation will help mitigate the risk of biases creeping into recommendations over time, thereby ensuring the model's reliability and effectiveness. The need for such testing introduces a novel perspective for future research endeavors, focusing on refining and expanding the applicability of hybrid decision-making methodologies in industrial settings.

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CONFLICT OF INTEREST

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