Enhancing industrial decision-making through ML-integrated frameworks and multi-criteria decision-making approach

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Abstract

Decision-making in contemporary industrial settings has evolved from intuition to data-driven methodologies, necessitating efficient handling of vast datasets. Conventional Multi-Criteria Decision Making (MCDM) approaches struggle with the complexities of big data. This study introduces an innovative decision-support system integrating multi-criteria methods with machine learning techniques as artificial neural network. 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 enhanced recommendations compared to traditional MCDM methods. While promising, future work must focus on robustness testing, particularly in real-time data dependencies, to ensure sustained efficacy and mitigate potential biases in recommendations over time.

Article Highlights

- Evolution of decision-making: From intuition to data-driven approaches.
- Challenges with conventional Multi-Criteria Decision Making (MCDM) in big data contexts.
- Introduction of an innovative decision-support system merging MCDM with machine learning.

1. 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 decision-making for industrial problems. 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. (Ewertz et al., 2009)

However, the efficiency of conventional MCDMs in providing valuable decisions based on the thorough assessment of alternatives is being hindered by their inefficiency in handling huge amounts of data related to multiple variables inherent in industrial processes given that contemporary processes are becoming increasingly data-driven, with the generation and consumption of large volumes of data (big data), making them both case-oriented and rule-based. (Tufegdžić, Milica, and Pravdić, Predrag, 2019).

Therefore, industrials are challenged to explore artificial intelligence techniques to consolidate heterogeneous data into actionable intelligence for resilient decision-making (Blanco-Novoa et al., 2018). Decision-making effectiveness 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.(Muñoz and Capón-García, 2019)

Recognizing the escalating demand for autonomous and efficient decisional intelligence, this paper introduces a new intelligent decision-support system that combines efficient multi-criteria decision-making approaches and soft computing. This novel approach presents a comprehensive six-step framework that leverages machine learning capabilities of identifying and earning patterns in large sets of data to support decision-makers in making optimal operational decisions while considering real-time performance data.

This paper is structured around five sections, in the first section, a state of art 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, and Section IV covers its testing. Finally, the findings are summarized in Section V, with suggestions for future research.

2. State of the art

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 necessitate data-driven techniques, in particular for condition monitoring. (Gokalp et al., 2016; Valdez et al., 2019) 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.(Duan and Da Xu, 2021). Hence data analysis is increasingly becoming at the heart of all industrial operations, notably decision-making.

To conquer the complexity of industrial decision-making problems 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 allow assessment of decisions with disproportionate and contradicting consequences, facilitating effective decision-making procedures. These methods serve as key for increasing involvement of stakeholders and instilling trust in decision-making by allowing pair-wise comparison of alternatives .(Taherdoost and Madanchian, 2023). In particular, the weighted sum approach remains fundamental in MCDM problems (Dos Santos et al., 2019a).

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.(Aziz et al., 2016; Munier and Hontoria, 2021; Wu and Tiao, 2018)

AHP offers a structured three steps process centered around numerical values through pair-wise comparisons (Dos Santos et al., 2019b). 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, relative importance of decision-making criteria is determined by quantifying their significance associated to 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.

$$CR = \frac{CI}{RI} \text{where} : CI = \frac{\lambda_{max} - n}{n - 1}$$

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

- CR < 0.1, the pair-wise comparisons are considered acceptable, indicating a satisfactory level of consistency.
- CR > 0.1, the pair-wise comparisons are deemed inconsistent and require reevaluation

- CR = 0, perfect pair-wise comparisons (Asadabadi et al., 2019; Saaty, 2008)

Table 1
Saaty's scale of relative importance

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 process 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 (Bertolini et al., 2021). Machine Learning is transforming decision-making in a variety of 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.(Jordan and Mitchell, 2015; Rai et al., 2021)

Supervised machine learning is widely used in industrial research due to its superior performance over unsupervised learning. (Silva and Bernardino, 2022). 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.(Biau, 2012; Speiser et al., 2019)

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.(Adedeji et al., 2019; Basheer et al., 2020; Kang, 2021; Prasad et al., 2019)

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. (Shafiei and Jazayeri-Rad, 2012) Research also suggests that ANNs can improve process management and control systems, although their effectiveness varies based on the situation at hand, (Khaouane et al., 2013). For Meddaoui et al. artificial intelligence 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."

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.

3. Decision-making methodology

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 (see Fig. 1).

3.1 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 enterprise. thereby, the setup entails the establishment of a tailored performance measurement system, considering that the effectiveness of decision-making is reliant 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 enabling decision-makers to assess all essential aspects together and spot whether an improvement in one area comes at the expense of another instead of focusing simply on financial aspects leading to suboptimization which can be detrimental to overall, as it had been the case using traditional systems.

- **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 for each of the four performance perspectives specified by the balanced scorecard method: financial, customer, internal business, and innovation and learning by answering 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**

The Fig. 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 where 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, as well as where it's headed while ensuring both the strategic and operational levels of the organization are operating simultaneously to ensure that all efforts are driving towards the same goal (Al-Adwan, 2018; Irawati, 2020). Before moving forward, a review session is conducted with managers and executives to verify that the BSC corresponds effectively with 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 and building upon the dataset gathered 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, consequently, determine their respective weights to establish the organization's overall performance function to be optimized while making-decisions (Fig. 3).

To perform AHP, 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**: Manager are required with the support of executives to determine the relative importance of different performance criteria with respect to overall goal using with 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 ration 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. They are tasked with brainstorming and developing a list of all possible solutions, even unconventional ones. To promote creativity and discovery, varied brainstorming approaches such as reverse brainstorming, mind mapping, word association, role-playing, and group brainstorming might be used to produce a wide range of alternative. The alternatives are compiled into a list after removing duplicate for reference in the following phases of the decision-making process.

- **Step 5: scoring alternatives**

The ultimate objective in optimizing a company's overall performance is to identify the alternative that maximizes the overall performance, even when these alternatives are not explicitly incorporated into the performance function. Their influence, however, directly affects overall performance. To address this challenge, the approach employs the scoring principle derived from the AHP method where executives are required to score each alternative's contribution to each specific performance objective with the help of the scale Table 1, which assists in quantifying the potential impact of each alternative on overall performance. Consequently, the selection of the optimal solution simplifies to choosing the alternative with the highest score.

The elementary scores reflecting the eventual impact of the alternative on each performance objective derived from the alternative scoring process are used to compute the overall score, which provides a holistic understanding of each alternative's performance across multiple criteria and serves to classify all the alternatives, providing a systematic approach to potentially identify and select the optimal course of action within the industrial context.

- **Step 6: alternatives evaluation**

The main aspect that distinguishes alternative evaluation in the context of industrial decision-making from other multi-criteria decision-making situations is the dynamic character of the significance associated with each alternative. The main challenge is that the impact of an alternative is not a static attribute; rather, it varies in importance depending on real-time variations in sub-performance levels related to performance objectives. Traditional Multiple Criteria Decision-Making (MCDM) approaches, which are commonly used in this sector, fail to account for the ever-changing dynamics of industrial performance. These strategies often presume a static process, focusing primarily on the possible impact of alternatives on performance objectives. Recognizing this limitation, the suggested alternative scoring approach provides a dynamic framework that accounts for real-time performance, resulting in a more flexible and context-aware decision-making approach designed to the complex nature of industrial decision-making.

The alternative score is evaluated using elementary score of alternatives against all performance objectives according to the equation below to determine the alternative amongst the potential options that maximizes the company's global performance most effectively:

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

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

The score calculation in our model is based on the potential impact of alternatives on performance goals, based on the decision-maker's judgement adjusted according to the current performance which makes the model responsive and dynamic, enabling more accurate and contextually relevant decision-making.

4. Intelligent decision-support system architecture and implementation

Industrial performance problems are often complicated and multidimensional, with a vast array of possible variables influencing output outcomes (Berrah et al., 2021). The method entails exploring machine learning techniques to alleviate the cognitive burden associated to the industrial decision-making process.

4.1 Choosing the machine learning method

The artificial intelligence module will serve as the decision-making brain as showed in the Fig. 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.

In the context of industrial performance, supervised machine learning is commonly employed (Kang et al., 2020), and, 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 a powerful data mining software to determine the more relevant 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. The alternatives were carefully defined and subsequently evaluated by experts across different performance contexts. 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 80% training set and 20% test set and used to train the 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 2.

Table 2
Accuracy of the three used models and test results

	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. Th 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.

4.2 Optimizing the ANN structure

The input and output layers of our ANN are already defined as system takes as input the scores of the alternative per performance objective (at 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 (see Fig. 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 general procedure to determine the optimal ANN architecture, the process is guided by some rule of thumb to determine the optimal number of neurons in hidden layers. In general, the number of hidden layers depend on the function the ANN will be serving, when the ANN is deigned 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 an arbitrary decision boundary to arbitrary 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 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. As per the number of hidden neurons, it should ideally fall between the size of the input layer and the size of the output layer, and the number of hidden neurons should be 2/3 of the input layer's size plus the size of the output layer, while also being less than twice the size 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.

As showed in Table 3 and Fig. 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.

Table 3
Mean square error results for different hidden layers configurations

2 hidden neurons	3 hidden neurons	4 hidden neurons	5 hidden neurons	6 hidden neurons	7 hidden neurons	8 hidden neurons	10 hidden neurons	12 hidden neurons	14 hidden neurons
7.40 E-04	2.12 E-07	4.77 E-04	5.82 E-04	5.76 E-04	2.30 E-03	1.30 E-03	1.70 E-03	2.20 E-03	1.90 E-03

5. Case study: Implementation of decision-making using AHP and Artificial Neural Network

in order to test the effectiveness of the method, we compared it with the widely utilized multicriteria decision-making method: the Analytic Hierarchy Process AHP, in an industrial setting.

5.1 Defining the decision-making framework

As mentioned in the Table 3, 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 3
KPI 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 perspective	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%	90%
	Obj11.Retain employees	Employee turnover	9%	2%
	Obj12.Engage employees	Employee participation rate	6%	20%

To complete the decisional framework, Key performance objectives comparison was done in multiple iterations with the participation of managers to prioritize KPOs and determine their respective weights until evaluation of the consistency ratio was validated with a CR = 0.1 falling inside the threshold.

objectives pair-wise comparison was done in multiple iterations until evaluation of the consistency ratio was validated with a CR = 0.1 falling inside the threshold, the hierarchical structure completed by the weights is as showed in the Fig. 7.

5.2 Understanding the decisional problem

The method is used to help the company decide on the optimal course of actions to take in order to face the problem of the increase in customer complaints the company have been experiencing recently due to product defects and quality issues in order to improve quality and reduce defects to maintain customer satisfaction and competitiveness and improve company’s overall industrial performance.

The company have 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.

5.3 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 assign a score using a structured and uniform assessment scale ranging for 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 solution turns to be efficient as cost savings realized.

1. The impact on the return on investment is neutral initially, potentially turning positive as benefits accrue.
2. The impact on the return on margin is neutral initially, potentially turning positive as cost savings are realized.
3. The impact on revenue growth rate 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 evaluation to ascertain their elementary scores, which are then summarized in table 4.

Table 4: 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

To validate the model and assess its capability to leverage real performance data, we conduct a comparative analysis. 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.

To validate the model and test its efficacy in utilizing real performance data, the comparison was conducted with the results obtained from the Analytic Hierarchy Process (AHP) in two distinct cases (two scenarios) featuring varying performance values.

- **Performance of case 1**:

Table 5
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

Referring to Fig. 8 and Table 5 pertinent to the case 1, 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.

- **Performance case 2**:

Table 6
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

As mentioned in Fig. 9 and Table 6, which are related to the second case, both 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 process to address indicating a strategic consideration of cost-effectiveness and resource allocation, focusing on resolving quality issues with limited financial resources.

6. Conclusions and future wok

In conclusion, the developed model represents a significant advancement in decision-making methodologies within industrial contexts. By 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 (MCDM) methods. The integration of Machine Learning (ML) 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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Author Contributions:

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by PhD student Hala Mellouli and Professor Meddaoui Anwar. Professor Zaki Abdelhamid examined the work and collaborated in its achievement.

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Figures

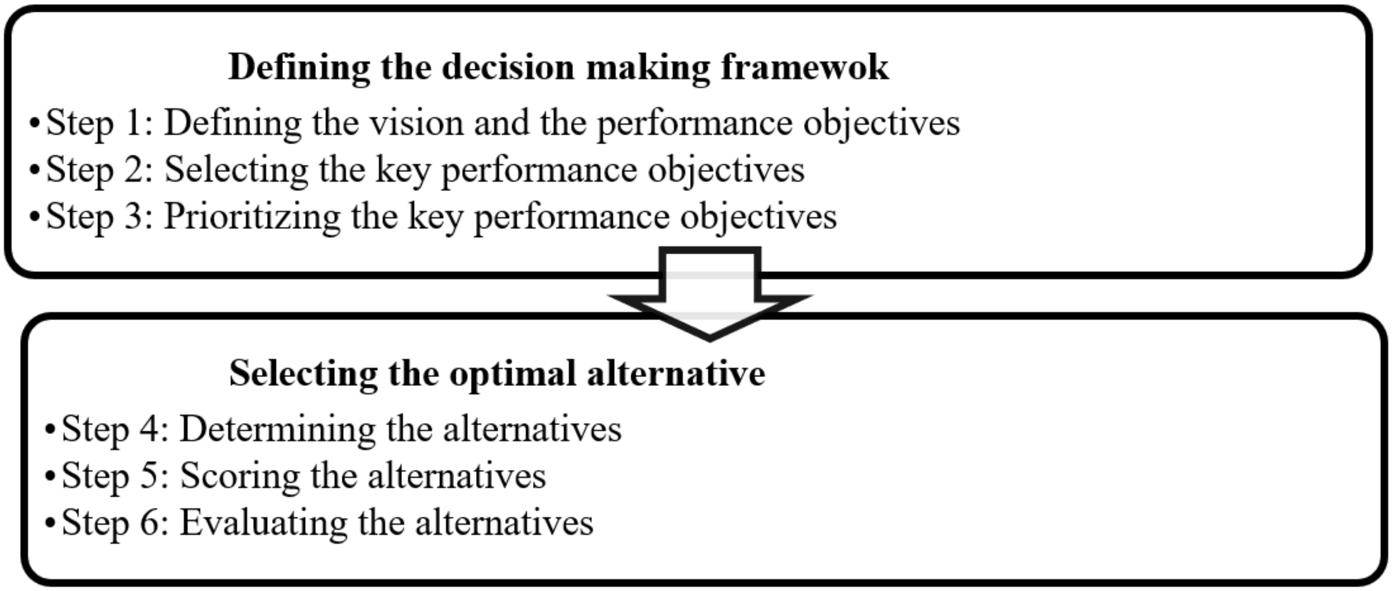

Figure 1

Decision-making methodology

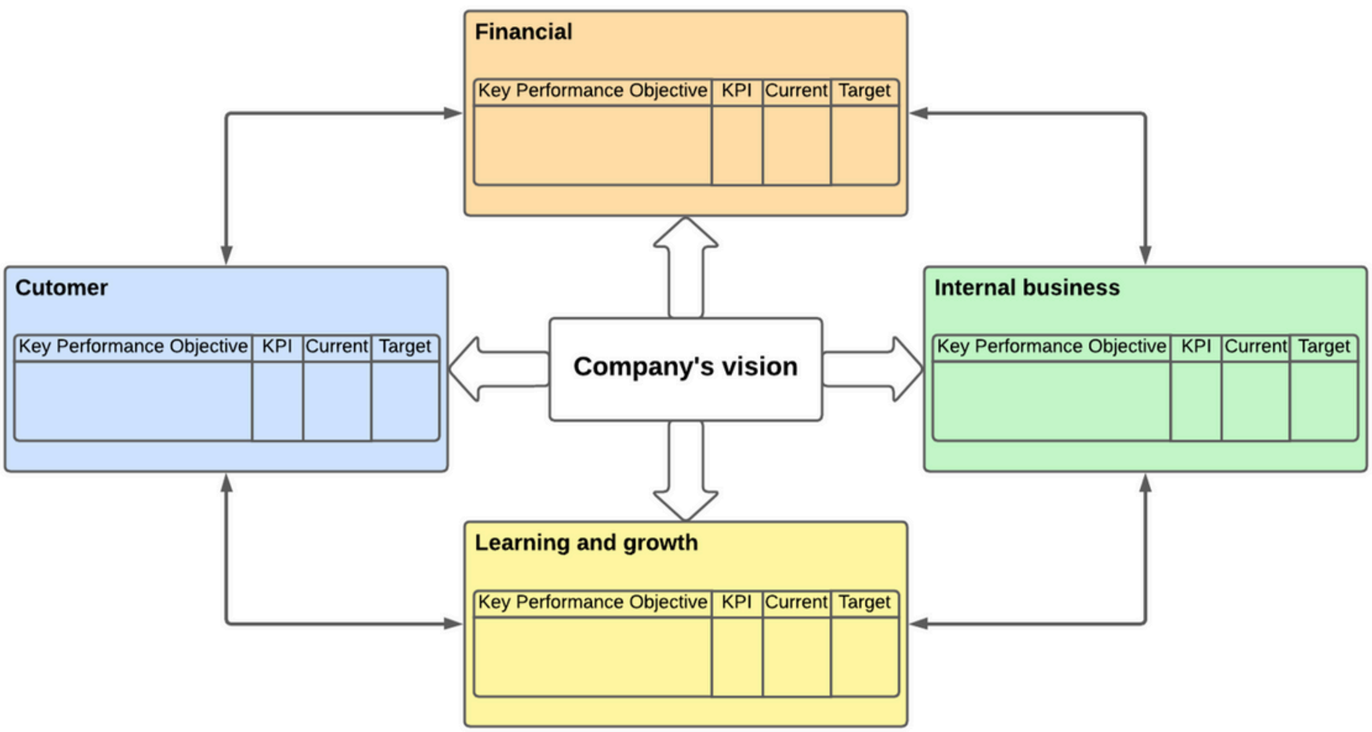

Figure 2

Balanced scorecard and KPI

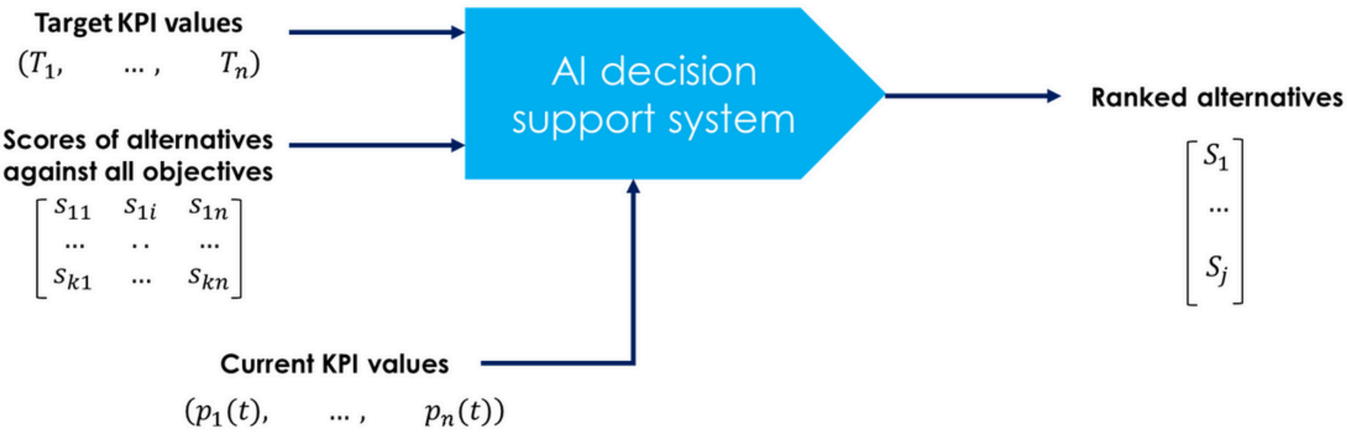

Figure 3

Decision-making hierarchy

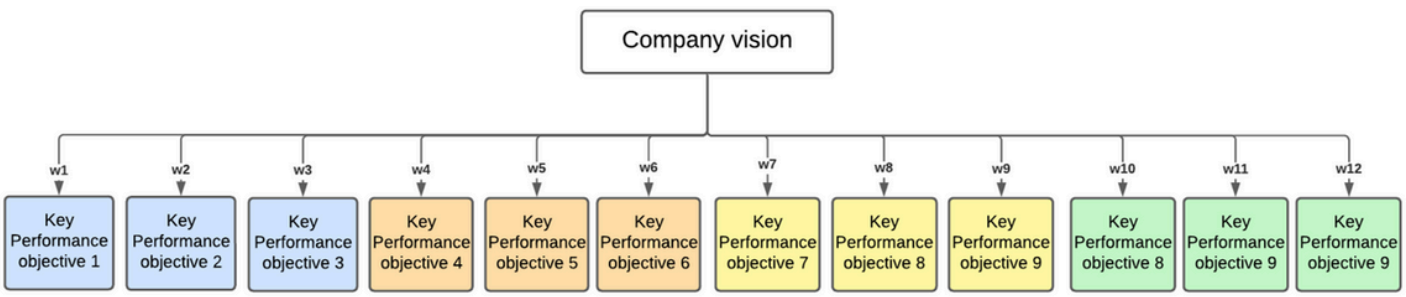

Figure 4

Decision-support system modelling

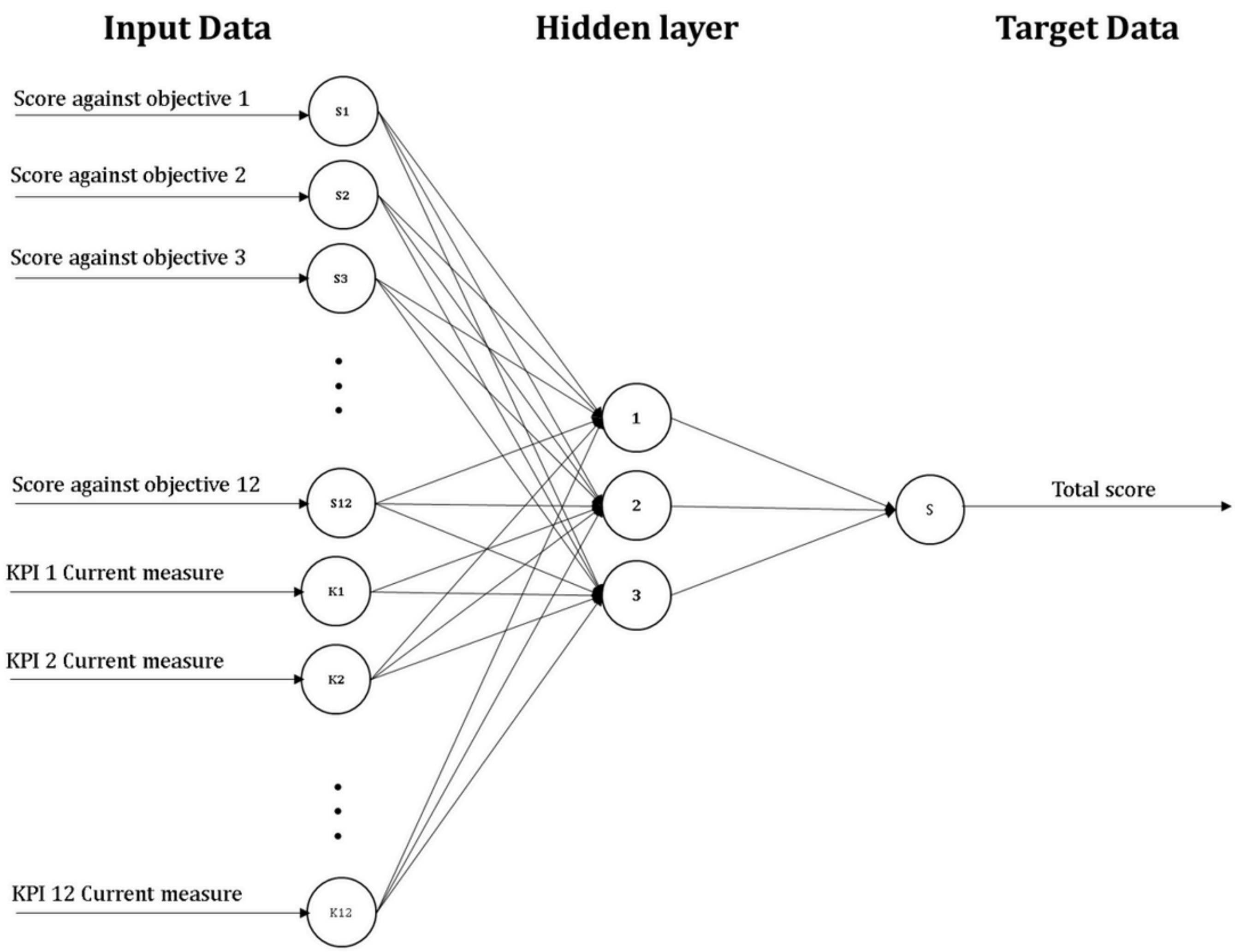

Figure 5

Optimized neural network structure

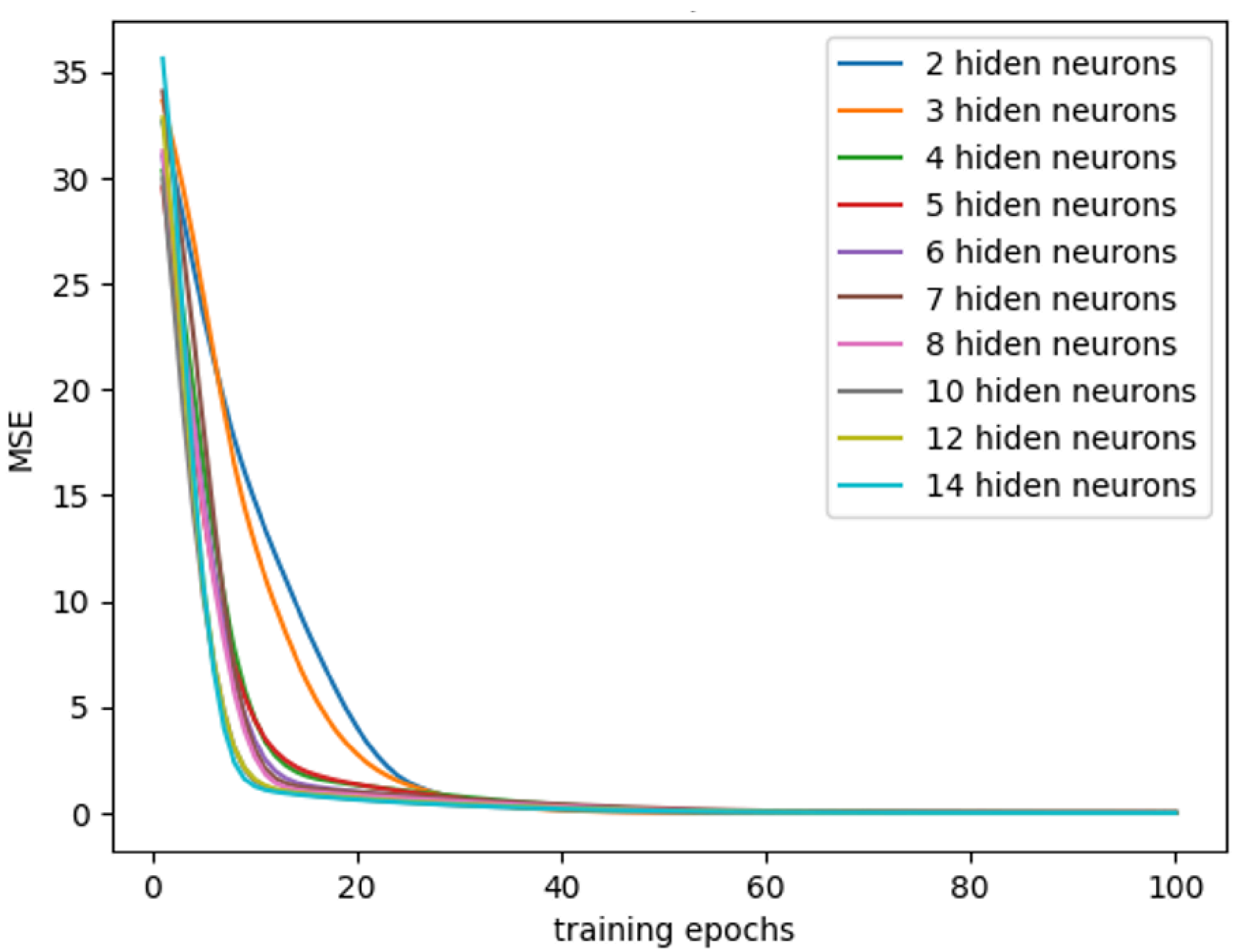

Figure 6

Training results for different hidden layers configurations

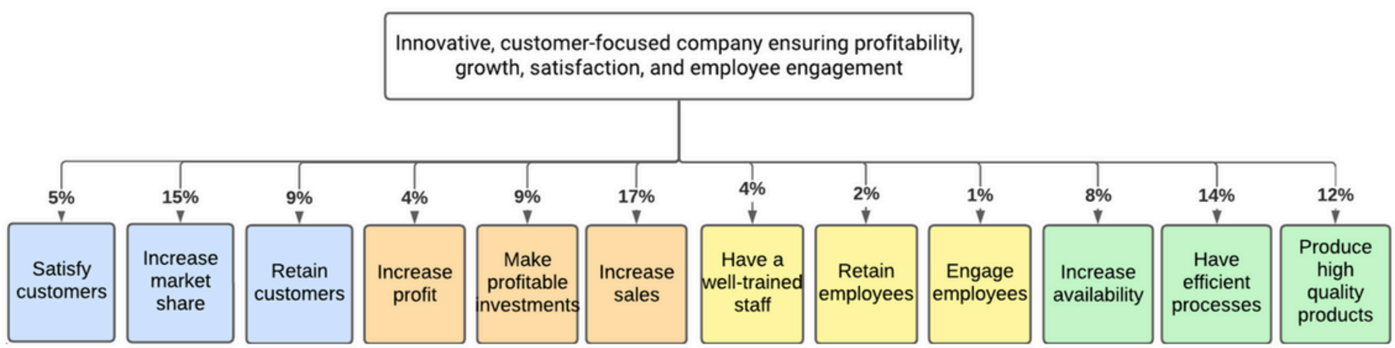

Figure 7

Decision-making hierarchy of a company operating in the automotive sector

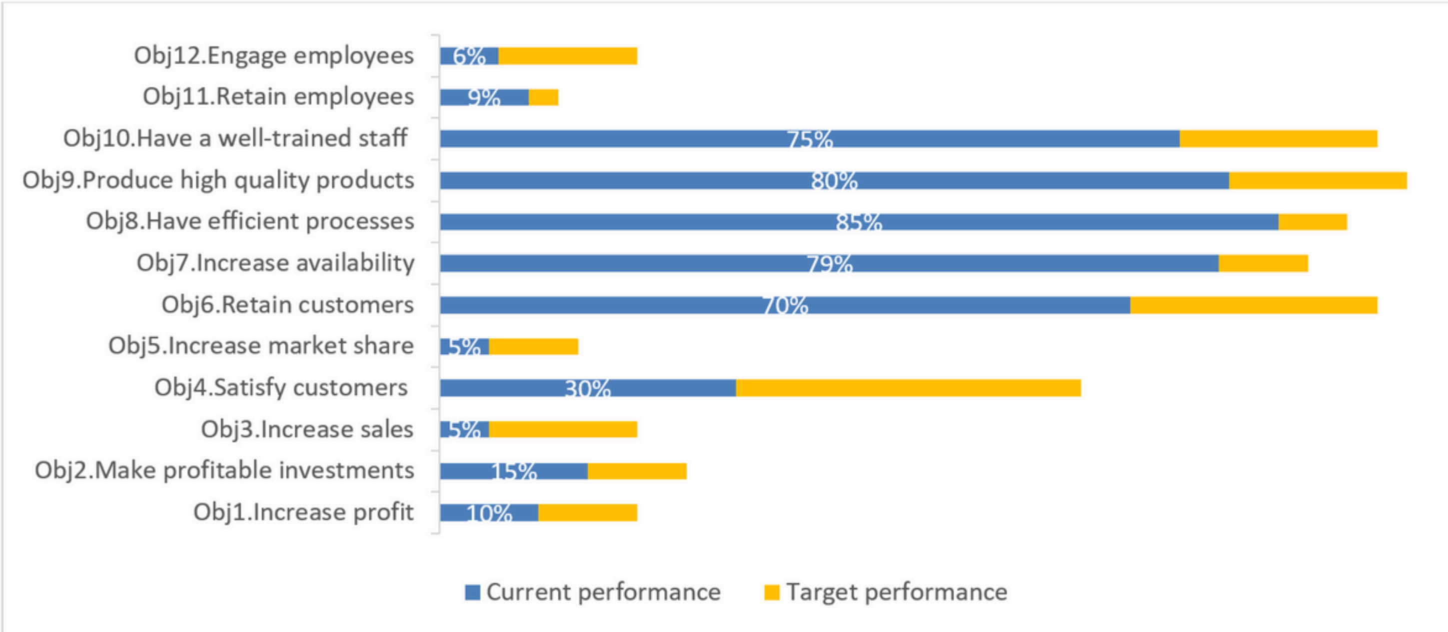

Figure 8

Case 1 performance

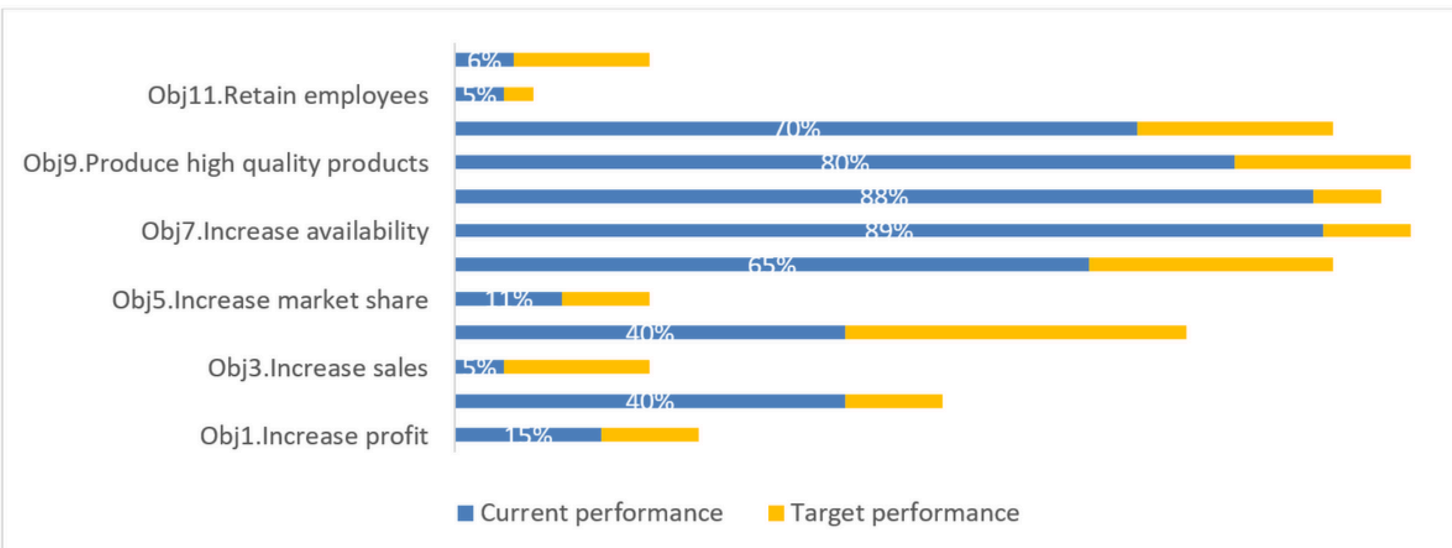

Figure 9

Case 2 performance