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A decision support system driven by artificial intelligence for industrial applications

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ABSTRACT

Decision-making in industrial settings is a continuous process that drives the organization's overall performance. It implies consistently selecting the optimal alternative, regularly reviewing the effectiveness of the decision, learning from its consequences, and refining the decision-making framework accordingly. in the modern era, characterized by the abundance of data, the ineffectiveness of conventional multi-criteria decision-making methods to process large volumes of data prevails over their ability to manage the multidimensional nature of decision-making in industrial settings, hence to cope with the increasing complexity of process industrials are challenged to explore the potential of artificial intelligence to optimize their decisions. In the current work, a new decision-making approach is introduced, the model combines artificial neural networks with the Analytic Hierarchy Process and the balanced scorecard to provide real-time decision-making recommendations for complex industrial problems.

Key words: Industrial performance, Artificial Neural Network, Analytical Hierarchy Process, Decision support system

I. INTRODUCTION

Multi-Criteria Decision Making (MCDM) covers a broad spectrum of methods and techniques specially conserved to select the best alternative among a given set of discrete options for highly complex problems. As a result, MCDMs were widely used to address various complex industrial problems [1] . Despite their diversity, MCDM approaches all adhere to a fundamental operational principle that begins with the selection of the criteria in alignment with the decision purpose, mutually independent, perceived on the same scale, quantifiable, and related to the alternatives. Afterward, the set of alternatives is built from realistic, available, comparable, applicable, and feasible options. Finally, the weighing and aggregation methods are determined [2].

Recognizing that it is a simple and powerful technique, the Analytic Hierarchy Process (AHP) is commonly utilized by decision-makers and academics. Indeed, Professor Saaty intended the technique to give a methodical systematic approach to synthesize, prioritize, and quantify a large number of factors enabling thus more efficient complex decision-making. that translates to the best possible extent of the decision-makers' understanding of the problem.[2, 3]. The method entails a 9-steps process:

1. Problem definition

- Identify the decision problem and the set of alternatives.
- Determine the criteria that will be used to evaluate the alternatives.

2. Construct the pairwise comparison matrix

- Create a square matrix that represents the pairwise comparisons of criteria or alternatives.
- Let n be the number of criteria or alternatives.
- Each element of the matrix represents the relative importance of one criterion or alternative compared to another.
- Let C = c_{ij} be the pairwise comparison matrix, where c_{ij} represents the relative importance of criterion i compared to criterion j.

3. Normalize the pairwise comparison matrix

- Normalize the matrix C by dividing each element by the sum of its column.
- Let $N = n_{ij}$ be the normalized matrix, where:

$$n_{ij} = \frac{c_{ij}}{\sum_{k=1}^{k=n} c_{kj}} \tag{1}$$

4. Calculate the priority vector

- Calculate the priority vector, denoted by w, by finding the eigenvector associated with the largest eigenvalue of the matrix N.
- Normalize the priority vector by dividing each element by the sum of all elements.
- Let $w = (w_1, w_2, ..., w_n)$ be the normalized priority vector, where w_i represents the priority weight of criterion i.

5. Calculate the consistency index (CI) and the consistency ratio (CR):

- Calculate the consistency index (CI) by using the formula:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{2}$$

where λ_{max} is the largest eigenvalue of matrix N and n is the order of the matrix.

- Calculate the consistency ratio (CR) by dividing the CI by the random consistency index (RI), which depends on the order of the matrix.
- If CR > 0.1, the consistency of the pairwise comparison matrix is considered questionable.

6. Perform the consistency check and revise if necessary:

- If CR > 0.1, review the pairwise comparisons and revise them until the consistency is achieved.

7. Calculate the weighted matrix:

- Calculate the weighted matrix, denoted by W, by multiplying the normalized matrix N by the corresponding elements of the priority vector w.
- Let $W = w_{ij}$ be the weighted matrix, where

$$w_{ij} = n_{ij} \times w_j \tag{3}$$

8. Calculate the priority values:

- Calculate the priority values, denoted by V, by summing the rows of the weighted matrix W.
- Let $V = (v_1, v_2, ..., v_n)$ be the priority values, where v_i represents the priority value of alternative i.

9. Rank the alternatives:

- Rank the alternatives based on their priority values, with higher values indicating higher priorities[4, 5]

While, MCDM techniques have captured the interest of both researchers and industrials in recent years, machine learning (ML) has made remarkable progress over almost the same time span, infiltrating many industrial processes [6]. Particularly in decision-making, artificial intelligence (AI) solutions are increasingly being used to reduce complexity and overcome cognitive burden, resulting in an intelligent decision support system capable of tackling intricate, imprecise, and poorly structured problems [7].

This paper is structured as follow: Section II introduces relevant work related to performance assessment and MCDM application while stressing the paper's contribution and originality. Section III describes the methodology's building components in depth. The outcomes of the suggested technique were then provided in section IV. Finally, Section V summarizes the findings and makes future recommendations.

II. Literature Review

In the literature, operational decision-making is associated with Multiple-criteria decision-making (MCDM), with research exposing a wide range of MCDM methodologies' applications to solve variety of decision-making problems within the industrial framework. The widespread use of AHP is primarily because it is one of the outperforming and easiest methods under MCDM that detects and minimize inconsistencies in opinion[8, 9].The Analytic Hierarchy Process (AHP), in particular, is being widely adopted to address a variety of decisional problems such as supplier selection considering criteria drawn from literature namely: price, quality, delivery and service divided into sub-criterions and weighted based on experts' opinions [10].

One additional use of MCDM techniques within supply chain management, combines both the AHP method and Complex

Proportional Assessment (COPRAS) approach for vendor selection, the framework considers the cost, the quality, the delivery time, and the service performance as criteria according to a review of the literature, and makes use of AHP to provide a hierarchical framework and determine criteria weights COPRAS is utilized afterward to rank alternatives and select the best option.[11].

Another example is IoT process selection that was similarly approached using the outputs of biometric literature review that revealed decision criteria namely: reliability, security, business, mobility, and heterogeneity as well as their respective weights [12]; AHP is also used to address maintenance strategy-related problems, such as determining which equipment shall be properly maintained first based on collected sensor data and weights computed using Bayesian Networks [13].

Although problem-centric applications of traditional MCDM methods provide interesting results when solving complex industrial problems, their efficiency remains questionable when considering their contribution to the overall performance given that decisions are made based on a narrowed set of problem-specific factors, which could lead to sub-optimization.

The complexity of industrial decision-making stems from not only the substantial number of factors on which it is dependent or the abundance of selections to consider but also from the requirement of consistency as well as coherence that must characterize all decisions because otherwise company's performance will be impaired from this vantage point, our suggested approach adds to the related literature by offering a generic intelligent framework for industrial decision-making that employs Balanced scorecard to establish evaluation criteria, AHP to compute their respective weights and Artificial Neural Networks (ANN) to overcome the complexity and cognitive burden of the decision-making process.

III. METHODOLOGY AND PROPOSED MODEL

Addressing these issues, this paper presents a holistic decision-making approach that efficiently combines BSC framework for converting corporate strategy into performance indicators [14] with the attributes of the AHP method to transcript the decision-maker's priorities and neural network feature of non-linear mapping capability. This allows coherent and consistent decisions to take place following the right course to achieve the overall goal of optimal performance.

1.1 Problem modeling

In this initial step, the decision-making framework is represented in a formalized way based on the Robert Kaplan and David Norton 's tried-and-tested balanced scorecard approach providing decision-makers with a quick yet comprehensive overview of the company. The decision-maker is required to clearly define the company's vision and strategy before breaking it down to less than 20 measurable objectives clustered into four performance perspectives namely:

- Financial perspective, ensuring the efficient use of financial resources;
- Customer perspective for consideration of customer satisfaction and needs;
- Internal business perspective in search of efficiency being the source of competitive advantages;
- Innovation and learning perspective, performance seen from the angle of human capital, information system and company's culture.[15, 16]

This first step, leads decision-makers to assess all essential operational KPIs together and spot whether an improvement in one area comes at the expense of another, preventing them from slipping into the trap of sub-optimization, which might be detrimental to the overall performance[15].

1.2 Objectif function

This second stage of the model aims to formulate the objective function which requires coefficients of the previously determined KPIs derived by Analytic Hierarchy Process in order to better adapt the model to specific decision-making contexts. Analytic Hierarchy Process is a multi-criteria decision-making technique developed in 1970s by Prof. Thomas Saaty to assist decision-making through pairwise comparisons of pre-defined criteria considered by decision-makers [4]. Statistics based on data gathered over decades reveal that AHP is the most commonly adopted approach worldwide mainly due to the simplicity of the algorithm and ability to reflect users' perceptions while solving complex problems [17].

The AHP algorithm rely on numerical scale to systematize and structure decision-making [18] according to the following steps:

- Step1: develop a hierarchical structure with the performance goal at the top level and objectives/ criteria at the second level and the alternatives at the third level.
- Step2: determine the relative importance of different criteria with respect to the goal.

Pair-wise comparison matrix is created with the help of Saaty's scale of relative importance

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

Pair-wise comparison matrix is then normalized to obtain criteria weights

- Step 3: evaluate the consistency

Before moving forward with analysis, the pair-wise comparison matrix is evaluated by means of the consistency index (CI) calculated using the largest eigenvalue (λmax) as per equation (2)

The obtained consistency index is afterwards divided by Random Index (RI)

$$CR = \frac{CI}{RI} \tag{4}$$

If the result is less than 0.1, the comparisons are acknowledged (perfect comparisons result in CR = 0) [5]

Table 2: Saaty's Random Index table

Matrix order n	1	2	3	4	5	6	7	…
RI	0	0	0.58	0.90	1.12	1.24	1.32	…

If result falls out of threshold, the comparisons are qualified inconsistent and returned to user for re-calculation or redeveloping the assessment [19, 20].

1.3 ANN model preparation and validation

At this point, the problem has been well defined and the resolution model using neural networks can be built. Artificial neural networks (ANN) are mathematical constructs that incorporate linked artificial neurons replicating the function of organic neural networks [21]. This machine learning model is becoming increasingly advantageous than convolutional regression and statistical models thanks to its efficient processing at high-speed [22].

The proposed model ANN predicts the best decision via a feed – forward artificial neural networks with back propagation training, it has a dynamic structure determined based on experience (trial and error method) depending on number of KPIs as there is no general procedure to find an optimal ANN architecture[21] .

The ANN is trained using a dataset containing alternatives scores per objective as well as current KPIs values against the overall score calculated using AHP method and adjusted considering actual performance to prioritize the objective with the biggest gap compared to the target.

IV. RESULTS AND DISCUSSION

This paper offers a holistic industrial decision-making framework built around artificial neural networks, the Analytic Hierarchy Process method, and the Balanced Scorecard approach to effectively exploit real-time performance data and provide relevant recommendations, thereby optimizing the decision-making process and, as a result, the industrial performance.

The model involves three steps: where the first step is modeling the decisional framework, which serves to clearly outline the complex real-world performance optimization challenge using the balanced scorecard, which assists the decision maker in defining the fundamental elements for decision making, starting with the problem statement, which describes the company's vision and strategy then the relevant variables derived from performance objectives, each with its own KPI, target, and deviation compared to the desired outcome.

The second step is defining the goal function based on the results of the previous stage. This entails carrying-out a pair-wise comparison of the objectives, the result of which is employed in building the objective function following consistency confirmation. As a result, the function is created with KPIs serving as inputs and the AHP analysis weights serving as coefficients.

The last step, which is optimization algorithm preparation and validation, builds on its precedents to create an artificial neural network that will be trained to encapsulate prior outputs as well as other relevant features for best decision prediction. While in operation, the model uses real-time performance data to provide an accurate recommendation.

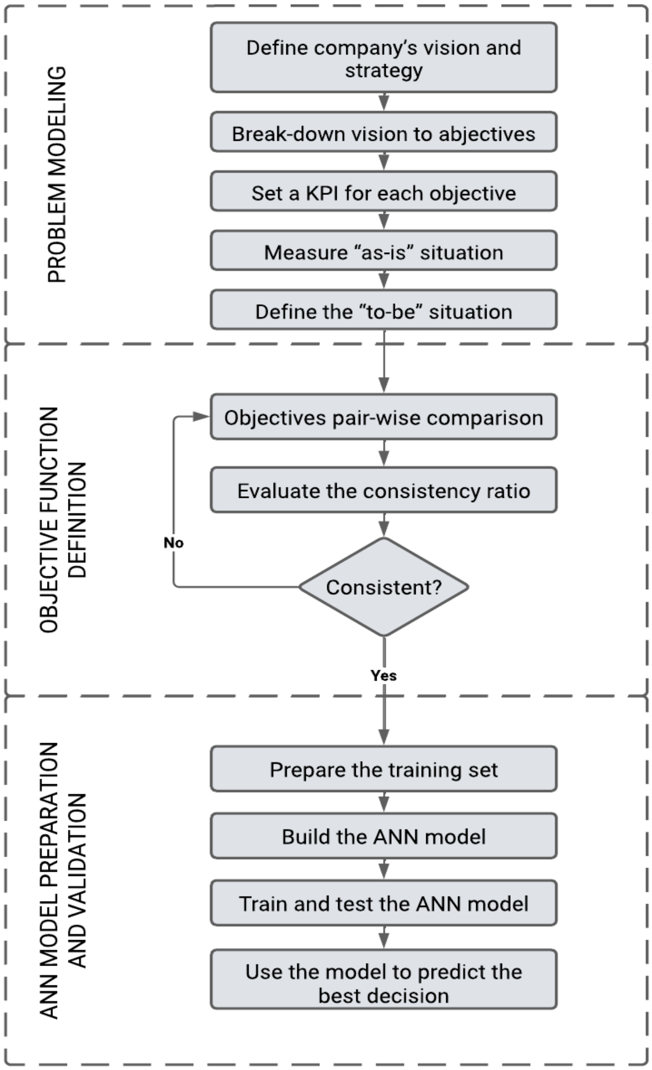

Figure 1: Flow chart of the decision support system implementation.

V. CONCLUSION

This study contributes to the literature with an intelligent decision-support approach intended for use within industrial context by first modeling the decision-making context through the definition of the important factors and their hierarchization in order to build the objective function prior to actually building a neural network capable of determining the most optimal solution. Industrial performance optimization is a complex process that involves choosing the most efficient options from a range of alternatives. Traditionally, this has been accomplished through a multi-criteria approach that considers multiple factors in the decision-making process. While this approach is effective to a certain extent, it has limitations that can impede its efficacy.

To address these limitations, this paper proposes a new methodology that builds upon the classic multi-criteria approach by incorporating the Analytical Hierarchy Process (AHP) and Artificial Neural Network (ANN) methods. By using AHP to classify decisions and actions, and coupling it with ANN to refine the most efficient possibilities, this methodology simplifies tasks for decision-makers and offers more precise solutions. Although this technique represents a substantial advancement in the optimization of industrial performance, it may still be enhanced by testing and improving its capabilities in the real-world using machine learning applications and simulations. By incorporating these technologies, the decision-making process can become even more precise and tailored to the specific needs of an industrial application.

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