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ENHANCING DECISION SUPPORT SYSTEMS THROUGH AI-DRIVEN ADAPTIVE WEIGHTING METHODS

Mirjana Misita[1], Neda Papic[1]
[1]University of Belgrade, Faculty of Mechanical Engineering, Belgrade, Serbia
e-mail: mmisita@mas.bg.ac.rs

Abstract: This paper presents an interactive-simulational framework for improving the determination of weighting coefficients in Analytic Hierarchy Process (AHP)-based multi-criteria decision-making. By integrating Monte Carlo simulation with Random Forest regression, the proposed method models uncertainty in user preferences and generates robust, personalized weight predictions without relying on extensive historical data. Experimental results on a case study with three criteria demonstrate that the approach preserves core priority structures while enhancing prediction stability and accuracy. The framework offers a flexible and adaptive solution suitable for AI-supported decision support systems, contributing to more reliable and transparent decision-making processes. Future research will explore expanded criteria and alternative machine learning techniques to further improve model performance.
Key words: AI-based decision support systems (AI-DSS); artificial intelligence (AI); decision support systems (DSS); Random Forest Regression.

INTRODUCTION

The Analytic Hierarchy Process (AHP) method belongs to the family of multi-criteria decision-making models with preference weighting (MCDM). The most frequently criticized aspect of this method in professional and scientific literature concerns the subjectivity involved in prioritizing criteria, specifically the assignment of weighting coefficients by the decision-maker, which is often cited as its greatest drawback. However, in individual decision-making situations, this characteristic can be seen as an advantage, as it allows customization of decisions according to the personal preferences of the decision-maker [1, 2, 3]. In the context of group decision-making or consensus building, generating weighting coefficients becomes a challenge and has been the subject of numerous studies. In response to this challenge, various modifications of the AHP method have been developed, such as fuzzy AHP, and others. This research examines the application of different artificial intelligence (AI) models in the automated generation of weighting coefficients and verification of results against expert assessments.
To overcome subjectivity in assigning weights within the AHP method, contemporary research increasingly explores the use of various AI models. One approach involves artificial neural networks (ANN), which, based on historical decision-making data, can learn prioritization patterns and independently generate weights, additionally, phase-AHP represents a significant modification of classical AHP by allowing the introduction of fuzzy and indeterminate values during the evaluation process, thus more adequately modeling uncertainty in the decision-maker's preferences [3, 4]. Within optimization techniques, genetic algorithms (GA) are used to search the space of possible weight configurations to determine the optimal combination satisfying defined efficiency and consistency criteria [5, 6].
Recent studies also explore the application of decision tree algorithms and techniques such as Random Forest, which can objectively assess the relative importance of criteria based on their frequency and significance in the past. With the development of deep learning, particularly through LSTM and transformer models, new opportunities arise for implementing advanced structures in multi-criteria decision-making, especially in systems involving temporal or textual decision dimensions. In the study by Heinrich et al. [7], three archetypes of AI-based decision support systems (AI DSS) are examined: systems based on generative models, explainable AI systems, and traditional machine learning algorithms without interpretability. The research aimed to determine how different user profiles evaluate the key characteristics of these systems in the context of high-risk industrial forecasting. The authors applied the Analytic

Hierarchy Process (AHP) method to quantify the relative importance of three decision criteria: system performance, implementation effort, and transparency. Participants (N = 69) performed pairwise comparisons among criteria and DSS archetypes, and the obtained weighting coefficients were analyzed according to user expertise level. Results showed that users in such contexts value system performance the most (with an average priority value of 0.47), while transparency was considered the least important (0.23), especially among more experienced users. Conversely, less experienced users exhibited a greater preference for transparent solutions. The study indicates statistically significant differences in preferences between different user groups, confirming the need for adaptive AI DSS systems that enable dynamic personalization of weighting coefficients based on user profiles. The findings provide empirical support for the use of the AHP method in automated weight generation within intelligent decision support systems.

In contemporary scientific and professional literature, the application of artificial intelligence (AI) in decision support systems (DSS) shows significant growth and diversity across various fields and industries. The work of Deliu and Chakraborty [8] highlights specific applications of AI-DSS in the field of precision and digital medicine, emphasizing how these technologies enable personalized and more efficient medical decisions. Similarly, Kose et al. [9] examine deep learning as a fundamental approach in medical DSS, providing a foundation for the development of intelligent systems in healthcare.

In the area of sustainable business, authors of research [10] emphasize the role of AI-DSS in supporting the circular economy, pointing to the potential of these systems to contribute to ecologically and economically sustainable decisions through resource and process optimization. This broader thematic perspective is further developed in the book [11], which presents a comprehensive overview of the latest advances in AI-powered DSS, including applications in medicine, urban studies, and industry, as well as the development of new decision-making methodologies.

The review [12] focuses on Industry 4.0, analyzing how AI integrates and enhances DSS through machine learning, deep learning, and natural language processing with the aim of improving supply chain management, predictive maintenance, and energy efficiency. A similar multidisciplinary approach is taken by Gupta et al. [13], who investigate the contribution of AI in operations research, emphasizing the necessity of synergy between theoretical models and practical applications in complex and uncertain environments.

A special place is held by the study of Kostopoulos et al. [14], who address the challenges and techniques of explainable artificial intelligence (XAI) in DSS, stressing the importance of transparency and interpretability of models to increase user trust and the quality of decision-making. This dimension of trust and ethics is further emphasized in the work of Kovari [15], who analyzes how accuracy and transparency are balanced in AI-DSS across various industries, highlighting key factors that influence the adoption and effectiveness of these systems.

Review studies clearly highlight the timeliness and growing importance of AI-powered decision support systems across different fields and point to the need for further research, particularly in areas of explainability, ethics, and user acceptance, to ensure broad and sustainable application of AI technologies in decision-making processes.

METHODOLOGY

In situations where historical evaluations of decision-maker (DM) preferences are lacking, this study proposes an interactive-simulational framework in which a Random Forest algorithm is trained on generated preferences derived from expert scripts and user responses to targeted preferential questions.

The choice of an appropriate machine learning model for predicting weighting coefficients within multi-criteria decision-making depends on several factors, including data complexity, dataset size, interpretability requirements, and noise robustness. Random Forest is often a suitable choice due to its robustness, ability to model nonlinear relationships, and resistance to overfitting. This model aggregates results from a large number of decision trees, enabling it to capture complex patterns in the data while providing relatively good interpretability through feature importance analysis.

However, depending on the problem specifics, other models such as Gradient Boosting Machines (e.g., XGBoost, LightGBM) may offer higher accuracy, especially on large and complex datasets, albeit at the cost of more careful hyperparameter tuning and less interpretability. Linear regression models or regularized approaches (Lasso, Ridge) may be more appropriate when transparency and simplicity are prioritized, though their ability to capture complex nonlinear relationships is limited. For small to medium-sized datasets, such as the simulated set considered here, Random Forest strikes a balance between performance and implementation simplicity. Its robustness to noise and ability to estimate prediction variability also make it well-suited for modeling variations arising from Monte Carlo simulation of user weights.

The thus constructed interactive-simulational framework enables prediction of weighting coefficients without relying on prior empirical data, thereby facilitating the generation and application of AHP models in contexts with limited experiential inputs. The proposed framework consists of four interrelated phases: interactive input of user preferences through pairwise comparisons, Monte Carlo simulation generating a set of realistic variations of weight vectors, training a Random Forest model on these simulated data, and finally generating precise and robust AHP matrices for decision-making purposes.

The experimental research plan through these four phases was realized as follows: after the user inputs their preferences via pairwise comparisons of criteria using Saaty's scale, the initial weighting vector is calculated by applying the standard AHP algorithm. However, to mitigate the potential subjectivity and variability in user assessments, the proposed framework incorporates an additional processing layer in the form of Monte Carlo simulation. This simulation generates a large number of weight vector variants based on the input preferences, maintaining the basic priority structure while introducing controlled noise to model realistic deviations in perceived criterion importance. The resulting set of simulated vectors is then used to train the Random Forest model, where the original user preferences serve as input variables and the corresponding weight variations as output target values. In this way, the developed model learns the patterns of relationships between user assessments and weight distributions, enabling prediction of stable and personalized weighting vectors for new users or similar decision-making contexts. Such a multilayer approach ensures greater robustness, resistance to extreme inputs, and a higher degree of adaptation to the decision-maker's profile, significantly improving the quality and reliability of multi-criteria evaluations within AI-supported decision support systems.

In practice, the proposed framework is intended to be integrated into an intelligent decision support system (AI DSS) via a simple and guided user interface, enabling its use by decision-makers without prior knowledge of multi-criteria methods or machine learning. In the initial phase, the user is asked a limited number of carefully designed preferential questions aimed at identifying their core value orientations regarding key decision criteria. Based on the provided responses and the specific problem context, the embedded Random Forest model, trained on simulated and structured data, automatically generates the corresponding weighting coefficients. The obtained values are then integrated into the AHP pairwise comparison matrix, which is used to rank available alternatives. The decision-maker is offered visual validation of the proposed weights and, if necessary, manual adjustment options with a display of the effects such changes may have on the final decision. In this manner, the system provides personalized, transparent, and methodologically sound decision-making even in conditions of limited empirical data, significantly enhancing the accessibility and flexibility of multi-criteria models across diverse domain-specific decision contexts.

EXPERIMENTAL STUDY

For the purpose of testing the methodological steps of the proposed interactive-simulational framework, a Python codebase was developed in this study utilizing modern libraries for data processing and machine learning, including pandas and numpy for data management, scikitlearn for implementing the Random Forest algorithm, and random for generating synthetic variations. The implementation is structured to cover all key phases of the methodology: interactive input of user preferences through pairwise comparisons of criteria based on Saaty’s scale, calculation of the initial AHP weighting vector, followed by Monte Carlo simulation generating a large number of realistic variants of this vector, and finally training the Random Forest model on the simulated data. The resulting trained model enables prediction of stable and personalized weighting coefficients for new users, based on patterns observed in the simulated variations, thereby providing flexible and adaptive support for multi-criteria decision-making. In this manner, the developed code enables experimental verification of the proposed framework’s ability to automatically generate AHP weights without requiring prior empirical evaluations, and forms the basis for its application within AI-supported decision support systems (DSS).

Within the experimental application of the developed model, testing was conducted on a single case study involving three criteria: performance, cost, and transparency. The user provided pairwise comparisons using Saaty’s scale, rating performance as significantly more important than cost (value 7), moderately more important than transparency (value 3), and cost as substantially more important than transparency (value 5). Based on these inputs, the initial weighting vector calculated using the AHP method indicated that the performance criterion holds a dominant weight of 0.6215, followed by cost with a weight of 0.2581, and transparency with the smallest weight of 0.1204. Figure 1 illustrates an example of the interaction with the decision-maker aimed at generating the initial weighting vector.

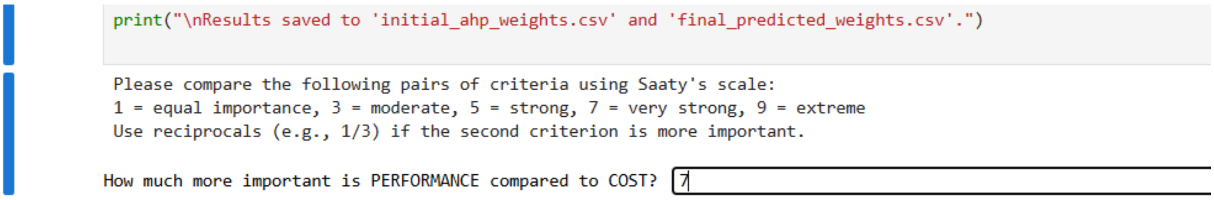


Fig. 1. *Interactive entry of the initial vector of weighting coefficients*

After the decision-maker provides ratings through pairwise comparisons of criteria based on Saaty’s scale, the initial user profile is transformed into a set of input features representing preferences in the form of discrete indicators. These input values serve as the primary data for training the Random Forest model. Subsequently, Monte Carlo simulation is employed to generate a large number of variations of the weighting coefficient vectors (Figure 2), which model potential deviations and uncertainties inherent in the user assessments. The generated variations constitute the target values, i.e., the output data to which the model adapts during the learning process.

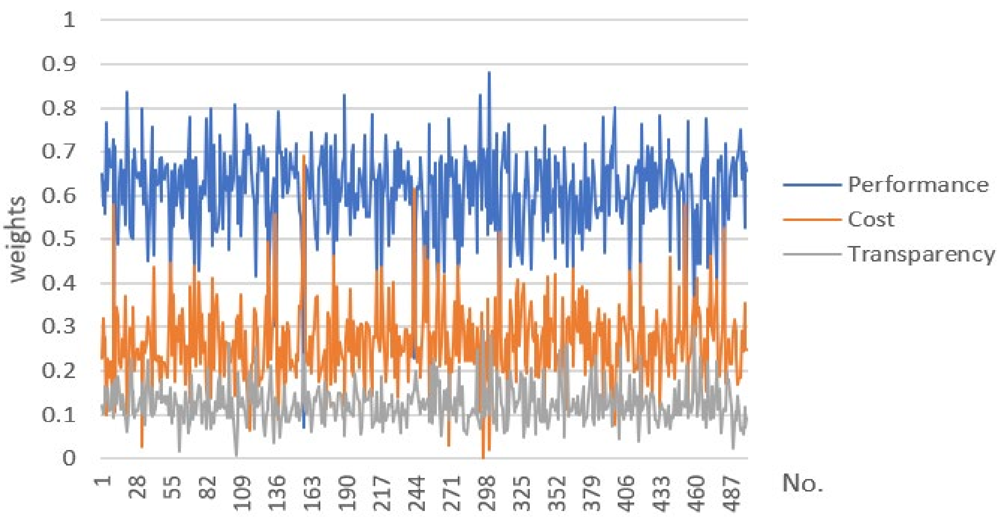


Fig. 2. *Monte Carlo weigths simulation results*

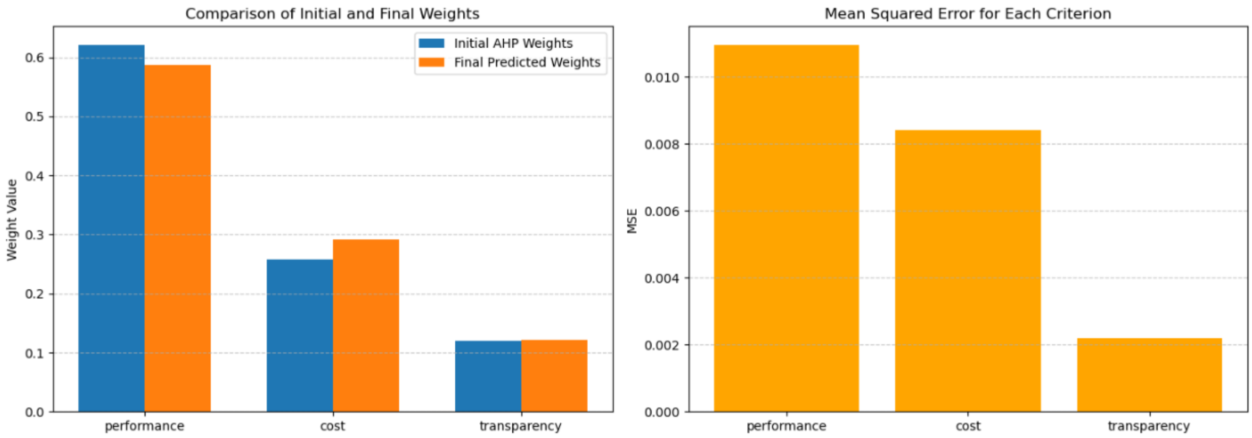
During the training phase, the Random Forest learns the relationships between user preferences and realistic distributions of weighting coefficients. A separate regression model is built for each criterion to predict its corresponding weight. This approach enables the model to generalize from the available simulated data and to generate stable and reliable weight predictions when new user inputs arise.
This methodology contributes to improving the accuracy and relevance of multi-criteria evaluations within artificial intelligence-based decision support systems.

```
# 9. SAVE RESULTS
pd.DataFrame([user_weights_dict]).to_csv("initial_ahp_weights.csv", index=False)
pd.DataFrame([final_weights]).to_csv("final_predicted_weights.csv", index=False)
print("\nInitial and final weights saved to CSV files.")
```

```
Please compare the following pairs of criteria using Saaty's scale:
1 = equal importance, 3 = moderate, 5 = strong, 7 = very strong, 9 = extreme
Use reciprocals (e.g., 1/3) if the second criterion is more important.

How much more important is PERFORMANCE compared to COST?  7
How much more important is PERFORMANCE compared to TRANSPARENCY?  3
How much more important is COST compared to TRANSPARENCY?  5

Initial AHP-derived weights:
performance: 0.6215
cost: 0.2581
transparency: 0.1204
Monte Carlo simulation set saved to 'monte_carlo_simulation_set.csv'
MSE for performance: 0.010959
MSE for cost: 0.008420
MSE for transparency: 0.002188

Final predicted weights by Random Forest:
performance: 0.5876
cost: 0.2915
transparency: 0.1208

Initial and final weights saved to CSV files.
```

Fig. 3. *Testing model of case study*

By employing a combined approach that integrates Monte Carlo simulation and Random Forest regression, the final predictions of weighting coefficients were obtained, which slightly deviate from the initial values derived by the AHP method: performance was estimated at 0.5876, cost at 0.2915, and transparency at 0.1208 (see Fig. 3). These results confirm that the model successfully preserves the core structure of user priorities, while simultaneously enabling a more robust and adapted estimation of weights that mitigates the effects of uncertainty and potential errors in assessments. Such characteristics of the model suggest its applicability in real-world decision-making scenarios, where precise and reliable determination of criterion weights is crucial.
To evaluate the model's accuracy, the mean squared error (MSE) was calculated for each criterion on the test dataset used for evaluating the Random Forest model after a 70/30 data split. The MSE values are moderate, with 0.010959 for performance, 0.008420 for cost, and 0.002188 for transparency, indicating a good level of prediction accuracy, but also some variability in results compared to previous experiments.



a) b)

Fig. 4. *MSE by criteria*

Figure 4a presents a comparison between the initial weighting coefficients obtained through the direct application of the AHP method on the user's pairwise preferences and the final weights predicted using the Random Forest model after a Monte Carlo simulation with an increased noise level. The chart clearly shows that the criterion "performance" dominates with a weight of approximately 0.62, reflecting a strong priority assigned by the user to efficiency or solution quality. The next most significant criterion is "cost," with a weight around 0.29, while "transparency" holds the lowest weight of approximately 0.12. It is notable that the final predicted weights slightly differ from the initial ones, indicating that the model introduces certain adjustments that contribute to increased robustness and stability of the weight estimations, while maintaining the fundamental preference patterns of the user.

Figure 4b displays the mean squared errors (MSE) of the model for each criterion, representing the average squared difference between the actual simulated and predicted weighting coefficients on the test dataset. The criterion "performance" exhibits the highest MSE value of about 0.011, indicating increased variability in predictions compared to earlier results, yet still demonstrating an acceptable level of accuracy. The MSE values for "cost" and "transparency" are lower, approximately 0.008 and 0.002 respectively, indicating solid accuracy of the model in predicting weights for these criteria. These values confirm that the model maintains good predictive capability even with the introduction of greater uncertainty through simulation.

CONCLUSION

This study addressed the challenges of subjectivity and uncertainty in determining weighting coefficients within the Analytic Hierarchy Process (AHP) for multi-criteria decision-making. Recognizing the limitations of traditional approaches that largely rely on expert judgment and static input preferences, an interactive-simulational framework integrating Monte Carlo simulation and Random Forest regression was proposed. This hybrid approach enables the generation of realistic variations in weighting vectors that reflect potential user uncertainty and facilitates the training of robust predictive models capable of adapting to new decision-makers' preferences.

The experimental evaluation conducted on a representative case study involving performance, cost, and transparency criteria demonstrated that the proposed model successfully preserves the core structure of user priorities while enhancing the robustness and stability of weight predictions. The achieved prediction accuracy, confirmed by moderate mean squared error values, indicates the model's effectiveness in managing the uncertainty inherent in user assessments.

Furthermore, the framework's adaptability and its capacity for personalized weighting underscore its practical applicability in real-world decision support systems, especially in contexts with limited historical data. By providing a flexible, transparent, and methodologically

sound mechanism for weight determination, the proposed approach contributes to improving the quality and reliability of AI-supported multi-criteria evaluations.
Future work may focus on extending the methodology by including additional criteria, exploring alternative machine learning models, and validating the approach across various application domains to further enhance decision-making efficiency.

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