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A Multi-Stage Approach for Evaluating and Selecting a Project Portfolio Based on Data Envelopment Analysis Under Uncertainty

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ABSTRACT

A project portfolio is a collection of ongoing or future projects within an organization, and its optimal selection—as one of the critical decisions in project management—contributes to optimal resource allocation and improved organizational performance. Accurate evaluation of projects for inclusion in the project portfolio is essential; due to various factors and uncertainties such as project duration, modeling these uncertainties is necessary to achieve optimal decision-making. In this study, uncertainties are modeled using an interval-valued fuzzy valuation method, which enhances the precision of the decision-making process. The present research proposes a three-stage method for optimal project portfolio selection under uncertain conditions. In the first stage, projects are scored using the Marcus multi-criteria decision-making method while considering uncertainties. In the second stage, project efficiency is evaluated through cross-efficiency data envelopment analysis while accounting for uncertainty. In the third stage, a multi-objective mathematical model is designed and solved for selecting the optimal project portfolio, which—beyond optimizing cross-efficiency scores and multi-criteria decision-making—maximizes the overall profit of the portfolio while satisfying budget, time, and workforce capacity constraints. The results indicate that combining these methods significantly improves decision-making accuracy and enables optimal project selection considering organizational constraints and objectives in complex and uncertain environments.

Keywords: project portfolio selection, data envelopment analysis, interval-valued fuzzy sets, project uncertainty

Introduction

Project portfolio selection has become one of the most strategically significant decision-making challenges in contemporary organizations, especially in environments characterized by uncertainty, resource constraints, and rapidly shifting competitive landscapes. With increasing complexity in organizational structures, technological developments, and globalized economic pressures, managers are compelled to adopt sophisticated, hybrid, and data-driven analytical frameworks that can integrate multidimensional criteria, risk factors, and interdependencies among projects. Traditional single-criterion or deterministic models have gradually become inadequate because project portfolios increasingly operate within highly dynamic, uncertain, and fuzzy environments where managerial judgments, stakeholder preferences, and performance indicators include inherent vagueness and ambiguity.

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Accordingly, scholars and practitioners have emphasized the use of multi-criteria decision-making (MCDM), fuzzy data envelopment analysis (DEA), cross-efficiency evaluation, and hybrid mathematical optimization techniques as robust alternatives for improving portfolio selection accuracy and organizational performance (1).

Numerous studies highlight that uncertainty has become a structural component of modern project environments. Factors such as fluctuating market conditions, ambiguous stakeholder expectations, risk interdependencies, environmental impacts, and dynamic technological changes significantly influence project performance, demanding the integration of uncertainty-handling tools in analytical models. The fuzzy set theory first introduced into industrial and management settings two decades ago provided a foundational basis for modeling ambiguity, imprecision, and subjectivity in managerial decision environments (2). Later research integrated interval-valued fuzzy numbers, triangular fuzzy numbers, and hybrid fuzzy-decision-making methodologies into portfolio selection, significantly improving the precision of evaluations and rankings, particularly when input and output data are vague or incomplete (3, 4).

Within this growing body of research, multi-criteria decision-making models have played an essential role in addressing the complexities of project assessment. The MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) method, one of the newest MCDM advancements, has been applied to evaluate performance indicators under uncertainty and to prioritize alternatives considering both ideal and anti-ideal solutions. Its adaptability in fuzzy environments and capacity to reduce human bias have made it a valuable tool in project selection settings (5). The use of MCDM techniques has been particularly beneficial when project criteria involve qualitative dimensions such as customer satisfaction, safety performance, sustainability impacts, and stakeholder value creation, all of which are subject to subjective assessments and nonlinear interactions (6).

Alongside MCDM approaches, data envelopment analysis has contributed substantially to efficiency evaluation and resource optimization. In environments with undesirable outputs, multiple inputs, and uncertain or incomplete data, DEA and its enhanced variants—such as cross-efficiency DEA, fuzzy DEA, robust DEA, and network DEA—provide deeper insights into project performance, efficiency scores, and benchmarking processes (7). DEA's ability to incorporate undesirable outputs and fuzzy data enhances its usefulness in project portfolio environments where factors such as delays, environmental impacts, cost overruns, or risk exposures may negatively affect overall portfolio performance (8). Hybrid fuzzy-DEA models, which combine fuzzy set theory with efficiency measurement, allow simultaneous treatment of uncertainty and performance evaluation, yielding more reliable results in volatile project environments (9).

Research has also focused on linking DEA with portfolio optimization procedures. Cross-efficiency DEA is particularly advantageous because it enables self-evaluation and peer-evaluation simultaneously, reducing bias associated with conventional DEA models and providing a more balanced performance score (10). When fuzzy environments are included, such cross-efficiency evaluation becomes more robust, especially in scenarios involving interval-valued inputs and outputs or ambiguous project resource requirements (11). Furthermore, hybrid approaches that integrate DEA with mathematical programming or integer optimization have demonstrated improvements in selecting optimal project combinations under uncertainty, enabling simultaneous maximization of efficiency, profitability, and resource utilization (12).

In addition to performance evaluation, modeling project interdependencies and risk propagation across portfolios has become a critical research priority. Recent studies emphasize that project portfolios are not merely collections of independent activities; instead, they embody complex networks of synergies, conflicts, and shared resource structures that directly influence performance outcomes (13). Revenue and cost synergies, technical dependencies, risk spillovers, and resource-sharing constraints must be explicitly incorporated into portfolio models to produce realistic and strategically aligned outcomes. Failure to model these interdependencies can lead to suboptimal portfolio structures, inefficiencies in resource utilization, and lost opportunities for synergy exploitation (14).

Hybrid optimization models integrating fuzzy logic, mathematical programming, and multi-objective frameworks have therefore evolved as effective tools in addressing these interdependencies. For example, combining MCDM methods such as MARCOS or TOPSIS with DEA and mixed-integer optimization enhances precision in ranking and selecting projects while satisfying constraints such as budget, workforce limits, scheduling requirements, and skill availability (15, 16). Furthermore, models utilizing sustainability and strategic dimensions—including environmental impacts, stakeholder value, and long-term corporate objectives—reflect evolving expectations for project portfolio management in modern organizations (6).

An emerging trend in project portfolio research is the development of dynamic and data-driven models that adjust to uncertainty over time. Such models address evolving project conditions, real-time performance fluctuations, and adaptive strategic requirements. Dynamic two-stage programming models, for instance, enable sequential evaluation and selection processes that reflect updated information and performance changes across project phases (15). These dynamic models improve decision-making accuracy and promote responsive planning in volatile environments, particularly in industries subject to rapid technological changes or fluctuating economic pressures (17). Similarly, the adoption of agile project management principles, especially in software development and public sector projects, underscores the need for adaptable, flexible, and iterative methods in project selection and execution (18).

As project teams become more diverse and distributed, human factors—including conflict management, communication quality, and organizational behavior—have increasingly been recognized as critical determinants of portfolio success. Poorly managed interpersonal dynamics and psychological conflicts within project teams can lead to delays, quality failures, and increased costs (19). Therefore, incorporating human resource management criteria—including skill availability, workforce training, and team stability—into project evaluation models is vital for capturing organizational readiness and execution capability. Contemporary project management frameworks emphasize the necessity of integrating human resource development into portfolio selection to align competencies with project requirements and improve organizational maturity (1).

In recent years, optimization models under fuzzy and uncertain environments have advanced significant methodological diversity in project portfolio research. Mathematical formulations using mixed-integer programming, multi-objective optimization, and hybrid fuzzy systems facilitate decision-making in contexts where conflicting goals—such as maximizing profitability, minimizing risk, and enhancing sustainability—must be simultaneously achieved (20). The integration of risk-adjusted metrics and fuzzy inputs in portfolio decision models also enhances the capacity to address oil projects, high-risk investments, infrastructure development, and technology projects with substantial uncertainty (14). Interval-valued fuzzy optimization provides an effective approach for capturing the full range of uncertainty and delivering more robust solutions compared to crisp or single-point estimates (3).

Furthermore, recent research concerning digital transformation, analytics-based strategy evaluation, and large-scale system optimization underscores the need for integrated project portfolio models capable of utilizing diverse data sources and employing advanced algorithmic structures. Studies show that digital analytics, when combined with strong project management practices, enhance strategic alignment and performance outcomes, particularly in sectors such as telecommunications and digital marketing (6, 21). As digital systems underpin increasingly complex organizational ecosystems, optimizing project portfolios in alignment with digital strategy becomes essential for maintaining competitiveness, agility, and stakeholder satisfaction. Although existing studies have addressed several of these challenges, there remains a need for comprehensive, integrated, multi-stage frameworks that combine the strengths of MCDM methods, fuzzy DEA evaluation, and multi-objective mathematical programming. Such frameworks should incorporate uncertainty modeling at every stage, account for resource limitations and interdependencies, and provide decision-makers with robust, data-driven insights grounded in both efficiency and strategic value (9, 11, 22).

The aim of this study is to develop a comprehensive multi-stage project portfolio selection framework under uncertainty that integrates fuzzy MARCOS evaluation, cross-efficiency fuzzy DEA, and multi-objective mathematical programming to optimize project selection based on efficiency, strategic value, and resource constraints.

Methods and Materials

This study, aiming to evaluate and select a project portfolio under uncertainty, proposes a three-stage approach that combines multi-criteria decision-making methods, data envelopment analysis, and multi-objective mathematical modeling. The rationale behind adopting this approach is the complexity of project selection in real-world environments, where multiple factors, conflicting criteria, and uncertainty prevail.

First Stage: Project Evaluation Using the Fuzzy MARCOS Method

The study first employs the MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) multi-criteria decision-making method, which was introduced in 2020 and operates based on ideal and anti-ideal reference points. This method performs exceptionally well in circumstances involving numerous criteria and uncertainty. Its primary advantages include comprehensiveness, flexibility, reduced human bias, process transparency, and suitability for group decision-making.

The inputs of this method consist of the decision matrix, criterion weights, criterion types (cost or benefit), and data types. In this study, interval-valued fuzzy data are used. The steps of the fuzzy MARCOS method include constructing the decision matrix, determining ideal and anti-ideal points, normalizing criteria, applying weights, calculating the utility of each alternative in relation to the best and worst conditions, and finally ranking projects based on the final performance index.

Second Stage: Cross-Efficiency Data Envelopment Analysis (DEA)

In the second stage, to achieve a more accurate assessment of project efficiency, cross-efficiency data envelopment analysis is applied. Unlike traditional DEA, this method considers not only self-evaluation but also the evaluation of each project from the perspective of all other projects. Employing a fuzzy version of DEA ensures that data uncertainty is also managed.

In this approach, α-level sets are used to convert fuzzy data into interval values. The efficiency of each project is calculated in two forms:

- Upper-bound efficiency (optimistic)
- Lower-bound efficiency (pessimistic)

These results are then incorporated into cross-efficiency models, and the final efficiency score of each project is obtained from the interaction of all units. In the ranking stage, the average of the upper and lower efficiency bounds is used to determine each project's final position.

Third Stage: Multi-Objective Mathematical Model for Project Portfolio Selection

In the final stage, a multi-objective mixed-integer linear programming model is designed to select the set of projects that yields the best combination in terms of profitability, efficiency, MARCOS scores, and resource productivity. The model includes three objective functions:

1. Maximizing profit obtained from executing projects
2. Maximizing MARCOS scores of projects
3. Maximizing DEA efficiency

The model also incorporates a series of constraints to ensure that project selection aligns with organizational realities. These constraints include:

• Human resource limitations
• Required project skills
• Employee training
• Workforce demand
• Project precedence relationships
• Budget limitations
• Avoiding simultaneous assignment of a worker to multiple projects
• Synergy effects among projects

Nonlinear constraints, such as skill requirements, are linearized so that the model can be executed with linear solvers.

To solve the multi-objective model, the goal-programming method is used, which minimizes normalized deviations from the goals of each objective. The payoff table is first prepared, and then the goal and worst-case scenario of each objective are determined. The model is solved as a single-objective model and implemented in GAMS using the CPLEX solver. Finally, for interval-valued fuzzy data, the process is repeated first for the inner triangle and then for the outer triangle to extract the best possible solution.

In line with analyzing and evaluating the MARCOS decision-making method, six key criteria identified in Figure (1) are defined as indicators of project success. These criteria include time, cost, quality, customer satisfaction, safety, and human resource management, each of which plays a central role in evaluating projects and determining the effectiveness of decision-making throughout the project lifecycle. These indicators were selected with precision so that their accurate measurement enables the examination of the effectiveness of project management approaches. In subsequent sections of this study, each of these criteria will be analyzed and explained in detail using collected data and associated analyses, enabling a precise understanding of how the MARCOS method contributes to project management effectiveness.

Figure 1. MARCOS Evaluation Criteria

Table 1, which is used as a tool in interval-valued fuzzy valuation, includes upper and lower bounds for each degree of quality. These levels consist of: very poor, poor, moderately poor, moderate, moderately good, good, and very good. The table helps determine the highest and lowest possible values for each quality level, enabling precise and objective analysis in contexts where decision-making relies on fuzzy data. Using this table in MARCOS model calculations is highly beneficial, particularly when dealing with uncertainty, as it allows decision-makers to compare and evaluate alternatives from a broader and more accurate perspective.

Table 1. Linguistic Comparisons

L (Lower Bound)	—	—	Linguistic Term	—	—	U (Upper Bound)
1	1	1	VP (Very Poor)	1	1	3
2	3	3	P (Poor)	2	3	4
3	3	5	MP (Moderately Poor)	3	4	5
3	3	5	F (Fair/Moderate)	3	5	6
5	5	7	MG (Moderately Good)	6	5	8
7	7	9	G (Good)	7	8	9
7	9	9	VG (Very Good)	7	9	10

Findings and Results

In this stage, the projects are evaluated using cross-efficiency data envelopment analysis. This analytical approach evaluates the relative efficiency of projects based on specified inputs and outputs. In this study, the main inputs include labor and cost, representing the resources consumed in each project. The outputs—return on investment and time—are used as criteria for measuring the performance and effectiveness of these resources in achieving project objectives. The use of this analytical model allows for a precise evaluation of the efficiency and effectiveness of the projects in comparison with one another and provides deeper insights into the strengths and weaknesses of each project. Such information is essential for informed managerial decision-making and optimal resource allocation.

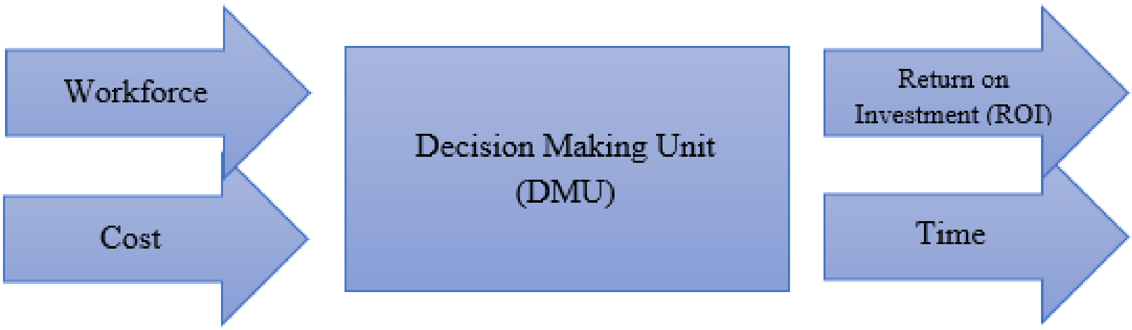

Figure 2. Inputs and Outputs of the Cross-Efficiency DEA Model

In this part of the study, the decision-makers determine the relative importance of each criterion for the various projects using Table (2), which contains the linguistic indicators. This table—which includes criteria such as time, cost, quality, customer satisfaction, safety, and human resource management—serves as the foundation for constructing the decision matrix in the MARCOS method. The decision matrix consists of two sections: one for the upper bound and another for the lower bound, allowing the MARCOS model to rank projects based on the assessed criteria. The MARCOS method makes it possible to ultimately provide an accurate ranking of projects based on the predefined indicators while considering the best and worst possible scenarios. This approach is highly applicable in complex and uncertainty-based decision-making environments and significantly assists in the strategic selection of projects.

Table 2. Linguistic Comparisons Provided by Decision Makers (DMs)

Options (Projects)	Time (C1)	Cost (C2)	Quality (C3)	Customer Satisfaction (C4)	Safety (C5)	Human Resource Management (C6)
A1	F	MG	MG	G	F	F
A2	VP	F	VP	F	P	VP
A3	MP	G	VP	F	VP	VP
A4	F	G	VP	F	VP	VP
A5	VP	VG	VG	F	VP	VP
A6	MP	VG	VP	F	P	VP
A7	P	VG	VP	F	VP	F
A8	F	MG	VP	F	P	P
A9	VP	MG	VP	F	MG	VP
A10	MG	F	VP	F	VP	P

The computations related to the MARCOS method, whose details are explained in Chapter 3, have been performed carefully and in accordance with the specified guidelines. The results obtained from these computations—which include interval-valued fuzzy evaluations and multi-criteria decision analysis—are presented in the following section. These results are provided for both the best-case and worst-case scenarios to enable a broader analysis of the influence of criteria on project ranking. This section not only provides the basis for further analytical examination but also enables decision-makers to make the best choices for future project implementation using precise and reliable data.

Table 3. MARCOS Evaluation Results – Lower Bound of Interval-Valued Fuzzy Numbers

Lower Bound	SI	KI-	KI+	FK-	FK+	F(KI)
A1	2.891273	0.045176	0.030758	0.405063	0.594937	0.024109
A2	2.445781	0.038215	0.026019	0.405063	0.594937	0.020394
A3	1.305971	0.020406	0.013893	0.405063	0.594937	0.01089
A4	1.282771	0.020043	0.013647	0.405063	0.594937	0.010697
A5	2.400879	0.037514	0.025541	0.405063	0.594937	0.02002
A6	1.430454	0.022351	0.015218	0.405063	0.594937	0.011928
A7	1.854987	0.028984	0.019734	0.405063	0.594937	0.015468
A8	1.831514	0.028617	0.019484	0.405063	0.594937	0.015272
A9	2.42641	0.037913	0.025813	0.405063	0.594937	0.020233
A10	1.953114	0.030517	0.020778	0.405063	0.594937	0.016286

Table 4. MARCOS Evaluation Results – Upper Bound of Interval-Valued Fuzzy Numbers

Upper Bound	SI	KI-	KI+	FK-	FK+	F(KI)
A1	2.74731	0.037126	0.029541	0.443114	0.556886	0.02184
A2	2.764495	0.037358	0.029726	0.443114	0.556886	0.021977
A3	1.539538	0.020805	0.016554	0.443114	0.556886	0.012239
A4	1.527571	0.020643	0.016425	0.443114	0.556886	0.012144
A5	3.001544	0.040561	0.032275	0.443114	0.556886	0.023861
A6	3.116295	0.042112	0.033509	0.443114	0.556886	0.024774
A7	3.476487	0.04698	0.037382	0.443114	0.556886	0.027637
A8	3.216795	0.04347	0.034589	0.443114	0.556886	0.025573
A9	4.208295	0.056869	0.04525	0.443114	0.556886	0.033455
A10	2.930903	0.039607	0.031515	0.443114	0.556886	0.0233

In this section, project efficiency is analyzed using the data envelopment analysis method with a cross-efficiency perspective. The data used are interval-valued fuzzy (IVF), where the inputs include “labor” and “cost,” and the outputs include “return on investment” and “time.” Each row of the table represents a project evaluated in terms of its input and output indicators. These data, shown in the, can assist in evaluating the performance of the projects and comparing their relative efficiency. By using data envelopment analysis and a fuzzy approach, it becomes possible to determine which projects make more optimal use of input resources and generate more desirable outputs. This evaluation enables decision-makers to identify and adopt the best projects to improve overall efficiency.

Table 5. Cross-Efficiency Data Envelopment Analysis Data

Case	Labor L	Labor M	Labor U	Cost L	Cost M	Cost U	Return L	Return M	Return U	Time L	Time M	Time U
Upper bound j01	4.2	4.4	6.8	22.1	26.1	29.7	0.132	0.159	0.165	30.7	34.3	39.5
Lower bound j01	4.3	4.4	5.9	23.2	26.1	28.1	0.141	0.159	0.161	32.2	34.3	39.5
Upper bound j02	4.3	4.5	6.6	20.7	22.3	32.2	0.122	0.145	0.163	32.3	35.2	46.4
Lower bound j02	4.4	4.5	5.9	21.3	22.3	29.1	0.136	0.145	0.154	33.7	35.2	44.8
Upper bound j03	4.1	5.3	7.9	22.2	24.4	25.4	0.125	0.151	0.165	38.3	43.0	45.3
Lower bound j03	4.7	5.3	6.4	23.1	24.4	25.1	0.138	0.151	0.161	39.2	43.0	44.9
Upper bound j04	5.0	5.6	7.8	21.0	27.9	28.1	0.126	0.134	0.162	32.8	43.2	46.4
Lower bound j04	5.3	5.6	6.8	24.5	27.9	28.0	0.129	0.134	0.156	33.7	43.2	45.6
Upper bound j05	5.6	7.1	7.3	22.5	23.5	24.4	0.140	0.145	0.168	37.2	42.6	44.4
Lower bound j05	5.9	7.1	7.2	22.9	23.5	23.8	0.143	0.145	0.156	38.6	42.6	43.5
Upper bound j06	4.3	4.5	6.8	23.5	24.1	31.8	0.134	0.145	0.162	30.3	32.7	39.1
Lower bound j06	4.4	4.5	5.3	23.8	24.1	30.2	0.138	0.145	0.158	31.2	32.7	38.1
Upper bound j07	4.5	4.7	6.7	23.4	24.6	26.0	0.133	0.146	0.155	31.7	36.1	47.1
Lower bound j07	4.6	4.7	5.3	23.8	24.6	25.7	0.141	0.146	0.151	33.6	36.1	39.6
Upper bound j08	3.8	4.1	4.4	30.2	31.2	33.3	0.128	0.134	0.165	33.0	41.7	44.6
Lower bound j08	3.9	4.1	4.2	30.8	31.2	33.1	0.129	0.134	0.157	35.6	41.7	43.4
Upper bound j09	4.6	5.0	7.3	21.7	24.0	30.1	0.122	0.133	0.164	44.1	45.7	46.6
Lower bound j09	4.8	5.0	6.7	22.6	24.0	29.3	0.129	0.133	0.146	44.9	45.7	46.1
Upper bound j10	6.5	6.9	7.7	23.5	28.1	34.8	0.148	0.156	0.163	30.8	38.2	41.6
Lower bound j10	6.7	6.9	7.1	24.6	28.1	33.7	0.151	0.156	0.161	33.4	38.2	40.3

The results of the cross-efficiency data envelopment analysis are presented in this section. In Chapter 3, the details of the computations and the method used were explained precisely. Here, the results of the calculations, which include the efficiencies computed for the upper and lower bounds, are reported. These results are analyzed in detail and are subsequently used as input to the objective functions in the final mathematical model. Ultimately, this mathematical model is designed with the aim of optimization and achieving maximum efficiency, and its results are shown in Table (6).

Table 6. Results of Cross-Efficiency Data Envelopment Analysis

Project	L	U
J01	0.789	0.897
J02	0.879	0.996
J03	0.808	0.996
J04	0.700	0.849
J05	0.746	0.921
J06	0.747	0.883
J07	0.786	0.906
J08	0.827	0.763
J09	0.828	0.943
J10	0.636	0.818

The third part of the study is devoted to the mathematical modeling of project selection, with the aim of achieving an optimal decision among the projects using mixed-integer linear programming. At this stage, a multi-objective optimization model is developed by taking into account the data obtained from the previous evaluation stages (MARCOS evaluation and cross-efficiency data envelopment analysis). The model is designed so that it simultaneously optimizes three key objectives: maximizing economic profit, enhancing workforce skills, and achieving optimal utilization of resources. To apply the model, all parameters, decision variables, objective functions, and related constraints are defined so that the existing limitations in resources, capabilities, and financial requirements are respected. This modeling stage helps decision-makers select a combination of projects that, in addition to economic efficiency, also have a positive impact on human resource development and create optimal synergy among projects. In the following, the data related to this stage and then the results of the solution method are presented.

The duration of project *i* represents the time to complete each project *i*. The data in Table (7) show the time required to complete each project and are used for the temporal analysis of the projects in the third stage of modeling.

Table 7. Project Durations

d(i,F)	Fuzzy Duration of Project *i*	L	M	U
I1		5.1	6.1	7.1
I2		6.0	7.4	8.8
I3		6.0	7.5	8.5
I4		5.2	6.5	7.8
I5		4.6	6.6	8.6
I6		4.0	6.2	8.4
I7		5.2	6.9	8.6
I8		4.9	7.3	9.7
I9		4.6	7.2	9.8
I10		5.1	7.9	10.7

The defuzzification method used in this study is based on the approach of Jiménez et al. (2007), which is recognized as one of the effective approaches for converting fuzzy values into crisp numbers. This method, by using a weighted average between the lower and upper bounds and adjusting the parameter α to balance these bounds, provides the necessary flexibility to incorporate uncertainties. In this way, the fuzzy value $d_i$is obtained from the combination of the mean of the lower and middle bounds and the mean of the middle and upper bounds, making it possible to provide a more accurate and consistent estimate of fuzzy values under uncertain conditions.

$$d_i = \alpha \frac{d_i^m + d_i^l}{2} + (1-\alpha)\frac{d_i^m + d_i^u}{2}$$

The cost of project *i*

The costs related to projects *i* represent the cost incurred for each project *i*. These data are used in the modeling for financial analysis and economic evaluation of the projects.

Table 8. Project Costs

C(i)	Cost of Project *i*
I1	150
I2	118
I3	119
I4	139
I5	120
I6	146
I7	106
I8	137
I9	102
I10	129

The revenue of projects *i* represents the income generated by each project *i*. The data in Table (9) show the revenue of each project and are examined in the third modeling stage for profitability analysis and financial return evaluation.

Table 9. Project Revenues

Income(i)	Revenue of Project *i*
I1	3025
I2	3003
I3	3201
I4	3260
I5	3315
I6	3113
I7	3198
I8	3138
I9	3076
I10	3469

The maximum number of personnel required for each project *i* is represented here. The data in Table (10) are used in the modeling for human resource planning in the projects.

Table 10. Maximum Employees Required for Projects

MP(i)	Maximum Employees for Project *i*
I1	31.2
I2	32.2
I3	33.2
I4	34.2
I5	35.2
I6	36.2
I7	37.2
I8	38.2
I9	39.2
I10	40.2

The average labor wage cost represents the average payment made to employees for performing work and is calculated by dividing the total wage cost by the number of employees or working hours. This indicator helps to gain a better understanding of the structure of labor costs in projects and enables cost comparison under different conditions.

Wage = 1000$

The available budget represents the total financial resources allocated and usable for project implementation. This data supports more accurate planning and financial management of the project and allows the researcher to incorporate financial constraints into decision-making and planning.

Bg = 700000$

Table (11) shows the precedence relationships among projects *i*. Each value in this table indicates whether project *i* must be completed before project *j* (value 1) or whether no such precedence is required (value 0). These data are used in the modeling for temporal planning and coordination among projects.

Table 11. Precedence Relationships among Projects

Pre(i,j)	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
I1	0	0	1	1	0	0	0	0	1	0
I2	1	0	1	1	1	1	0	1	0	0
I3	0	0	0	0	0	0	0	1	1	0
I4	0	0	0	0	0	1	0	1	0	0
I5	1	0	1	1	0	0	0	0	0	0
I6	0	0	1	1	0	0	1	1	1	0
I7	0	0	1	1	0	0	0	0	0	1
I8	1	0	0	0	1	0	0	0	0	0
I9	0	1	0	0	0	0	1	0	0	0
I10	0	0	0	0	0	0	0	0	1	0

The above table shows the magnitude of cost synergy effects between projects *i*. Each entry τ(*i,j*) represents the magnitude of the cost impact that the simultaneous implementation of project *i* and project *j* in a project portfolio can have on one another. These data are used in the modeling process to analyze and optimize the combination of projects and to manage costs.

Table 12. Cost Synergy Effects Between Projects

τ(i,j)	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
I1		0.31	0.04	0.82	0.23	0.41	0.30	0.44	0.72	0.59
I2	0.31		0.13	0.16	0.32	0.57	0.27	0.04	0.69	0.67
I3	0.04	0.13		0.33	0.76	0.18	0.68	0.67	0.83	0.52
I4	0.82	0.16	0.33		0.28	0.56	0.41	0.07	0.81	0.33
I5	0.23	0.32	0.76	0.28		0.08	0.57	0.02	0.74	0.91
I6	0.41	0.57	0.18	0.56	0.08		0.56	0.47	0.72	0.51
I7	0.30	0.27	0.68	0.41	0.57	0.56		0.89	0.77	0.14
I8	0.44	0.04	0.67	0.07	0.02	0.47	0.89		0.26	0.68
I9	0.72	0.69	0.83	0.81	0.74	0.72	0.77	0.26		0.45
I10	0.59	0.67	0.52	0.33	0.91	0.51	0.14	0.68	0.45	

Table (13) shows the magnitude of revenue synergy effects between projects *i*. Each entry η(*i,j*) represents the magnitude of revenue impact that the simultaneous implementation of project *i* and project *j* in a project portfolio can have on one another. This information is used in the modeling process to optimize the combination of projects and increase revenue returns.

Table 13. Revenue Synergy Effects Between Projects

η(i,j)	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
I1		0.58	0.72	0.68	0.02	0.84	0.71	0.16	0.61	0.66
I2	0.58		0.19	0.36	0.62	0.73	0.41	0.16	0.01	0.01
I3	0.72	0.19		0.95	0.98	0.97	0.86	0.14	0.05	0.55
I4	0.68	0.36	0.95		0.18	0.99	0.81	0.31	0.09	0.43
I5	0.02	0.62	0.98	0.18		0.35	0.12	0.59	0.45	0.41

I6	0.84	0.73	0.97	0.99	0.35		0.91	0.21	0.22	0.54
I7	0.71	0.41	0.86	0.81	0.12	0.91		0.63	0.33	0.15
I8	0.16	0.16	0.14	0.31	0.59	0.21	0.63		0.93	0.25
I9	0.61	0.01	0.05	0.09	0.45	0.22	0.33	0.93		0.06
I10	0.66	0.01	0.55	0.43	0.41	0.54	0.15	0.25	0.06	

Table (14) shows the skill requirements of projects *i*. Each entry skill(*i*,*k*) indicates the level of need of project *i* for skill *k*. These data are used in the modeling process to optimally allocate human resources and to plan for the provision of the skills required by projects.

Table 14. Skill Requirements of Projects

skill(i,k)	K1	K2	K3	K4	K5
I1	2	4	3	2	2
I2	2	3	4	2	3
I3	4	3	4	4	2
I4	3	2	2	4	3
I5	3	3	2	2	3
I6	4	2	3	4	2
I7	2	3	2	4	2
I8	2	3	4	3	3
I9	3	2	2	2	3
I10	2	3	3	4	2

The mathematical model developed based on the explanations and full structure presented in Chapter 3 has been solved using the GAMS optimization software. This model includes several components, such as scheduling and optimal selection of the project portfolio, management of precedence relationships among projects, allocation of workforce to projects, and analysis of skill matching. The model also examines the skills required for each worker and the skills acquired by individuals and specifies the number of trained individuals in each skill. The results obtained from this model, which are presented below, are used to optimize project performance and human resource productivity.

The designed mathematical model contains parameters subject to uncertainty, represented by interval-valued fuzzy data. The interval-valued fuzzy data in this model consist of two inner and outer triangles with a common height of 1. The solution process is as follows: first, the problem is solved using the inner triangle. At this stage, in the first objective function, the lower bounds of efficiency obtained from data envelopment analysis are used, and in the second objective function, the lower bounds of the weights obtained from the MARCOS method are considered. For defuzzifying the inner triangle, the method of Jiménez et al. (2007) is used. In the next step, similarly, the outer triangle and the upper bounds of efficiency values and MARCOS weights are considered. The only difference at this stage is that the optimal value from the first step is taken as the lower bound in the second step to ensure improvement of the solution in this step.

Table (15) shows the results related to the starting times and selection of the project portfolio. This table presents the scheduled start times for each project in the final portfolio based on the solution of the mathematical model and helps to optimize project planning and execution.

Table 15. Scheduling and Portfolio Selection

	T1	T10	T13	T17	T20	T27
I1					1	
I5			1			
I6				1		
I7		1				

I8	1	
I9		1
I10		1

The results related to the skills required for each worker are presented. This table shows which skills *k* each worker *e* needs in order to participate effectively in the projects. This information helps to optimize human resource allocation and to identify training needs for enhancing employee productivity.

Table 16. Required Skills for Each Worker

	K1	K2	K3	K4	K5
E1	1		1		
E2		1	1		1
E3	1			1	1
E4	1	1	1	1	1
E5	1	1	1	1	1
E6	1			1	1
E7		1	1	1	
E8			1	1	1
E9	1	1	1	1	1
E10	1	1	1	1	1
E11	1	1	1	1	1
E12	1			1	1
E13	1	1	1	1	1
E14	1	1			
E15					1
E16					1
E17					1
E18	1			1	
E19	1	1	1	1	1
E20			1	1	

Table (17) presents the results of the model related to the skills acquired by the workforce. This table shows which skills *k* have been acquired by each worker *e*. This information is useful not only for assessing the current capabilities of employees but also for training planning, as it helps identify training needs and determine the required training programs to improve skills and increase productivity.

Table 17. Skills Acquired by the Workforce

	K1	K2	K3	K4	K5
E4	1			1	
E5		1		1	
E9			1		
E11		1	1	1	
E13		1	1		
E19		1	1	1	1

Table (18) presents the results related to the number of trained individuals in each skill. This table shows, for each skill *k*, how many employees have received the necessary training. This information is essential for training planning, improving the distribution of skills, and ensuring the availability of a skilled workforce for project requirements.

Table 18: Number of Trained Individuals in Each Skill

Skill	Number of People
K1	1
K2	2
K3	4
K4	5
K5	2

The presented charts show the results of the sensitivity analysis of the defuzzification parameter α in the third stage on the three objective functions Z_1, Z_2, and Z_3. This analysis examines how the values of the objective functions change in response to different values of the parameter α and helps to assess the impact of this parameter on the overall performance of the model. As can be seen in the charts, changes in α lead to different variations in the optimal values of the objective functions, such that for some values, the performance of the objective functions improves, whereas for other values, it deteriorates. This information can be used to select an appropriate value of α to achieve optimal model performance and to support more precise decision-making.

Figure 3. Sensitivity analysis of the defuzzification parameter α on the first objective function

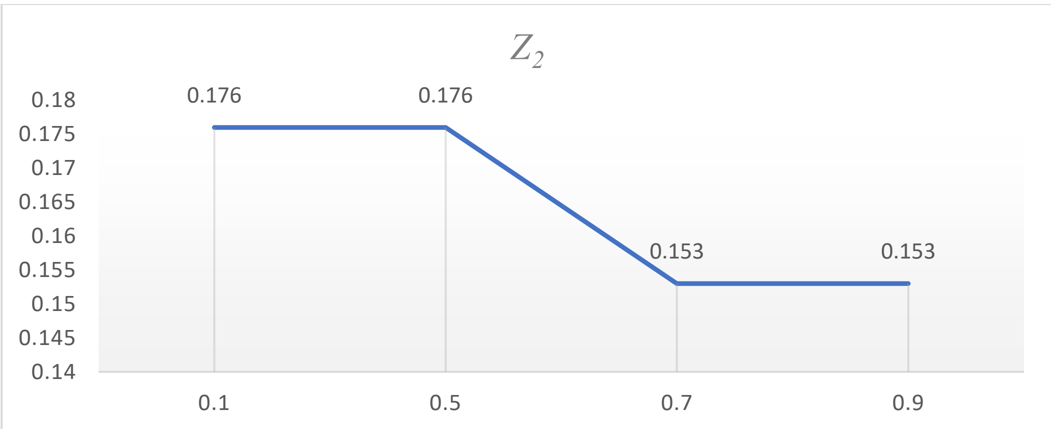

Figure 4. Sensitivity analysis of the defuzzification parameter α on the second objective function

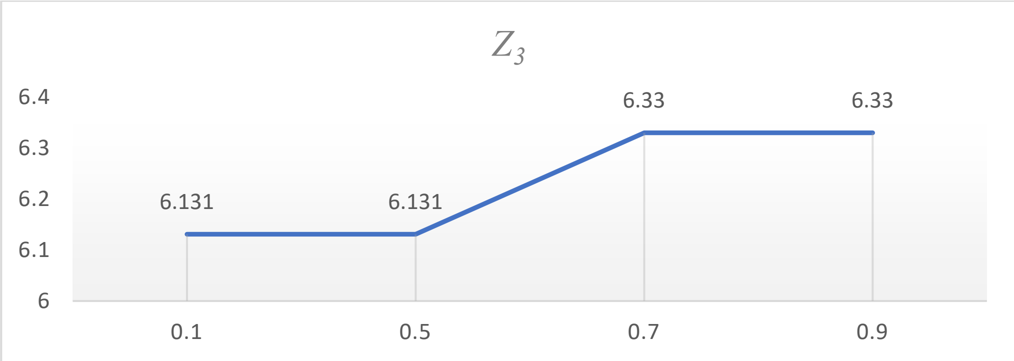

Figure 4. Sensitivity analysis of the defuzzification parameter α on the third objective function

The presented charts show the results of the sensitivity analysis of the defuzzification parameter α in the DEA model on the objective functions. This analysis examines the effect of changes in α on the optimization results of the model's objective functions and helps to obtain a better understanding of the stability and sensitivity of the model with respect to this parameter. As can be seen in the charts, variations in α can lead to significant changes in the optimal values of the objective functions, and this information is important for fine-tuning and effective optimization of the model.

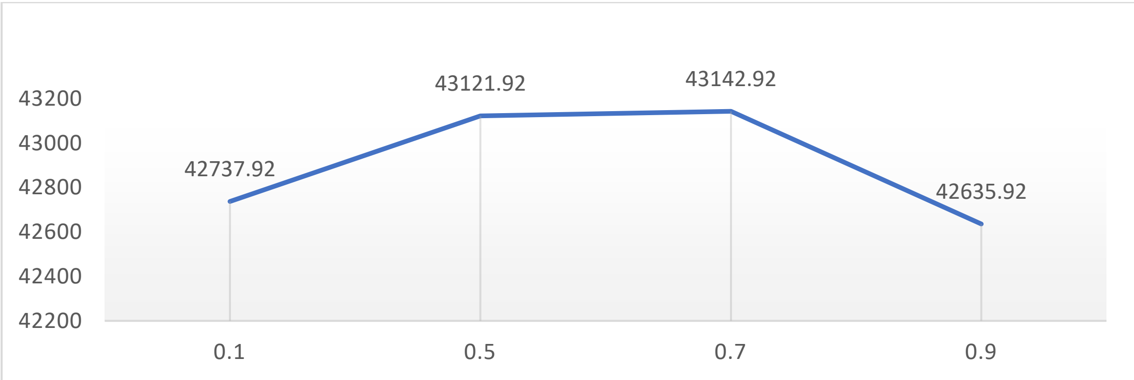

Figure 6. Sensitivity analysis of the defuzzification parameter α in the DEA model on the first objective function

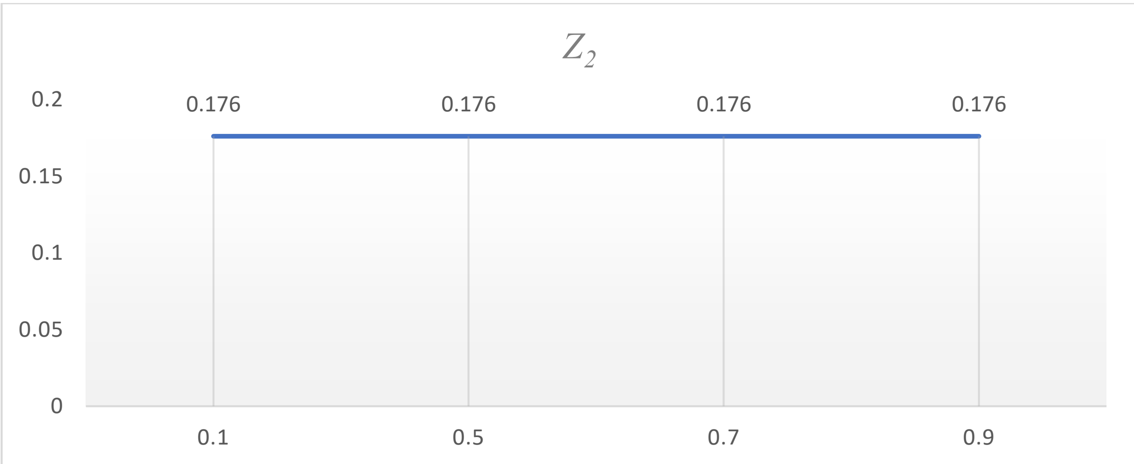

Figure 7. Sensitivity analysis of the defuzzification parameter α in the DEA model on the second objective function

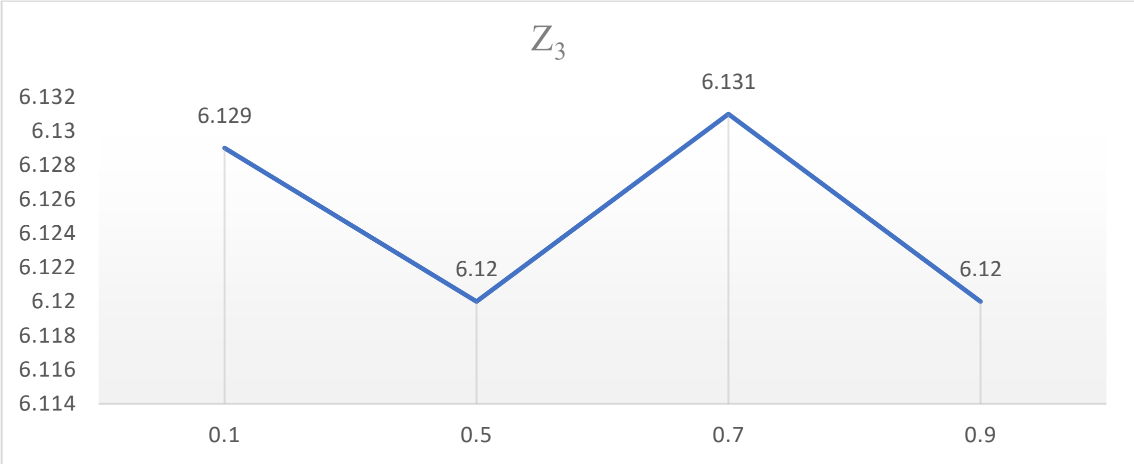

Figure 8. Sensitivity analysis of the defuzzification parameter α in the DEA model on the third objective function

The presented chart shows the effect of changes in the labor wage cost parameter on the profit objective function Z_1in the third stage of the model. This sensitivity analysis investigates how changes in labor costs, from a decrease of 0.2 units to an increase of 0.2 units, influence the profit value. As can be seen, with an increase in wage cost, the value of the profit objective function decreases. This result indicates the importance of controlling labor costs to optimize project profitability and provides valuable information for financial decision-making and resource management.

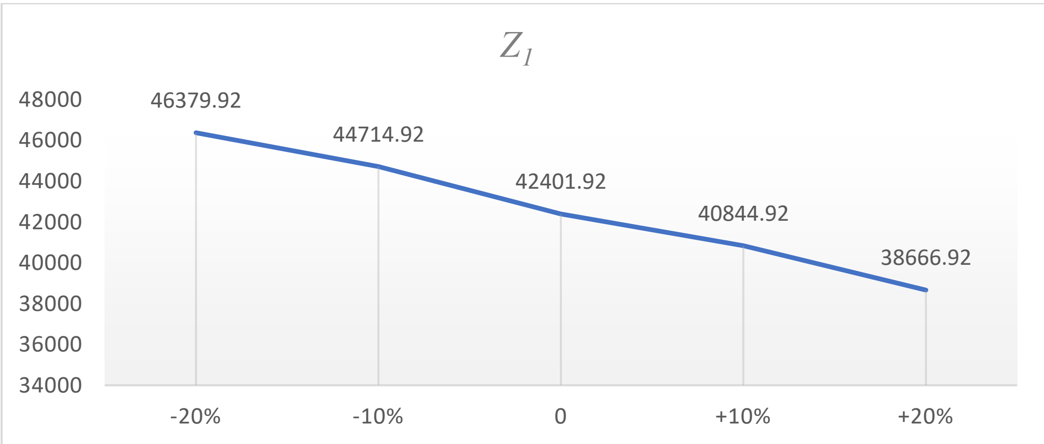

Figure 9. Sensitivity analysis on the labor wage cost parameter

Sensitivity analysis on the available budget parameter in the third stage on the objective functions

The presented charts show the results of the sensitivity analysis of the available budget parameter in the third stage on the three objective functions Z_1, Z_2, and Z_3. This analysis examines the changes in the values of the objective functions in response to different values of the budget parameter and helps assess the impact of this parameter on the overall performance of the model. As seen in the charts, changes in available budget cause fluctuations in the optimal values of the objective functions, such that increases or decreases in budget have a direct effect on the profitability and efficiency of the model. This information is important for managerial decision-making in resource allocation and in setting an optimal budget for projects.

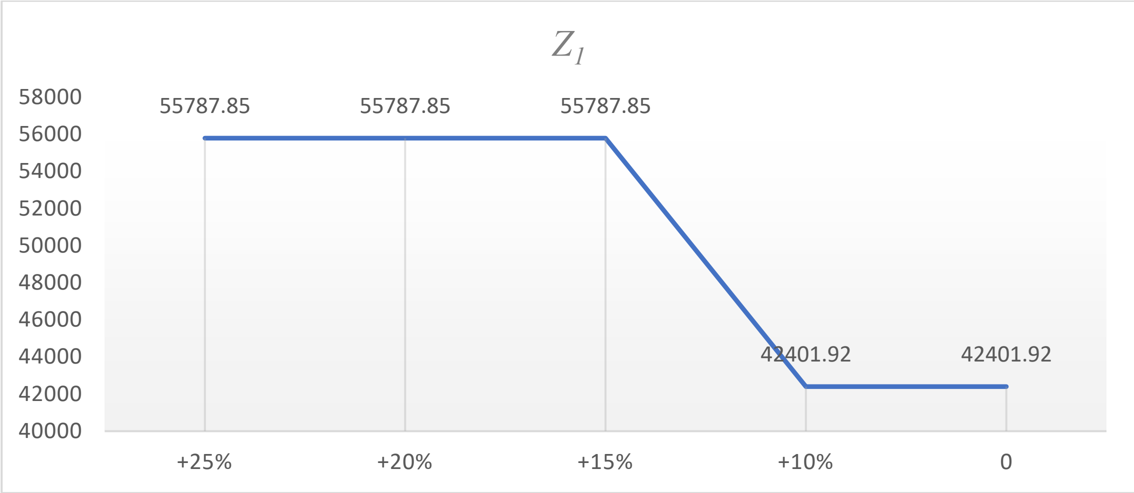

Figure 10. Sensitivity analysis on the available budget parameter on the first objective function

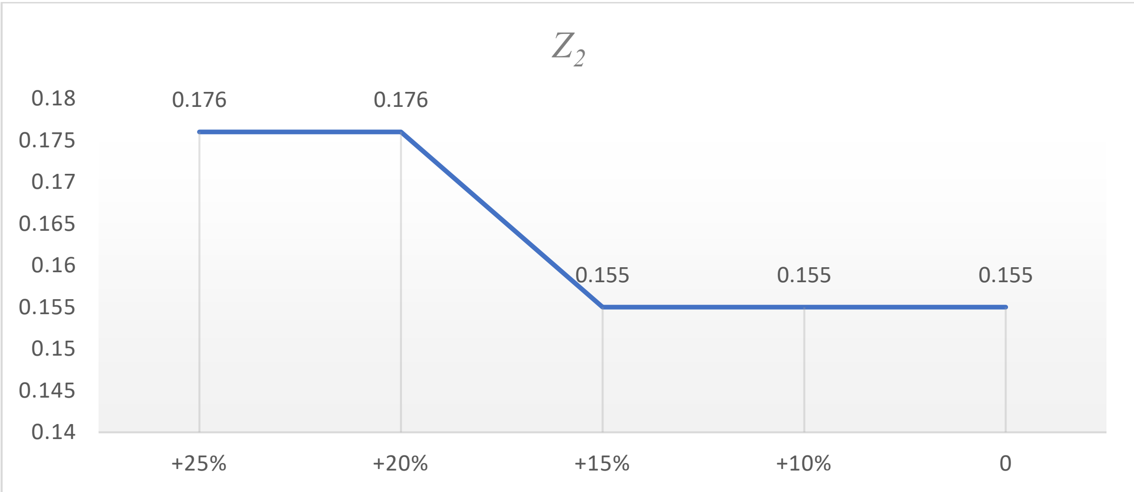

Figure 11. Sensitivity analysis on the available budget parameter on the second objective function

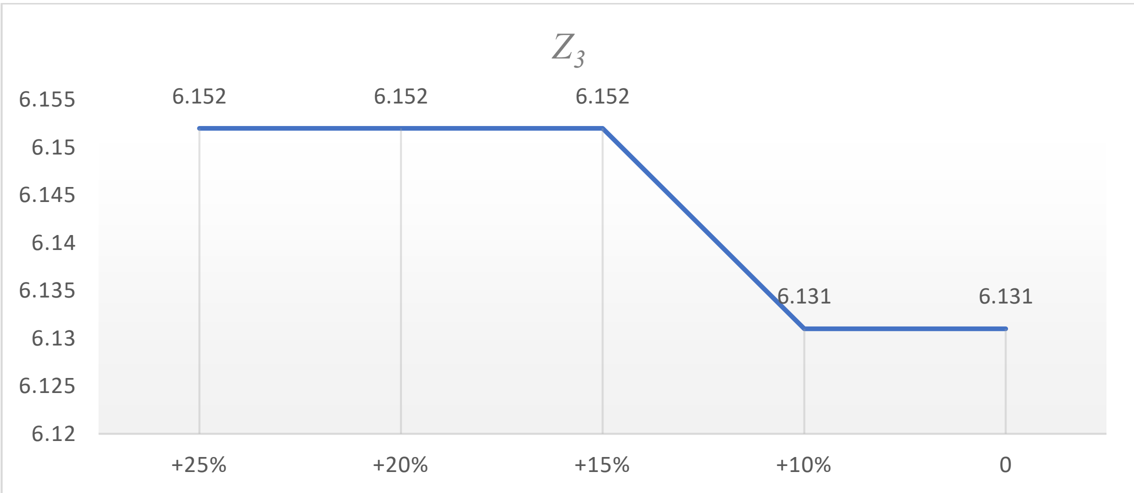

Figure 12. Sensitivity analysis on the available budget parameter on the third objective function

To investigate the effect of changes in the criterion weights on the final results, various swaps among the criterion weights were performed, such that the weights of each pair of criteria were interchanged and each new combination of weights led to different results. This procedure was used to identify the effects of weight changes on the final results and to allow for the assessment of the stability of the results and the degree of sensitivity of the model to weight swaps. The results obtained from each swap were recorded and indicate the model's sensitivity to changes in the weights of the criteria and their impact on the final ranking of projects. This analysis is particularly useful for a better understanding of the decision-making model and has been conducted for both the upper and lower bounds.

Table 19. Sensitivity Analysis of MARCOS Weights for the Upper Bound

Upper Bound	First & Second	First & Fourth	Second & Fourth	Second & Sixth	Third & Fourth	Third & Fifth	Fourth & Fifth	Fifth & Sixth
A1	0.0223	0.0225	0.0245	0.0264	0.0264	0.0218	0.0221	0.0224
A2	0.0246	0.0200	0.0222	0.0219	0.0219	0.0224	0.0219	0.0220
A3	0.0129	0.0123	0.0137	0.0136	0.0136	0.0123	0.0122	0.0125
A4	0.0128	0.0122	0.0136	0.0135	0.0135	0.0122	0.0121	0.0124
A5	0.0272	0.0219	0.0253	0.0253	0.0253	0.0223	0.0238	0.0241
A6	0.0221	0.0248	0.0203	0.0191	0.0191	0.0252	0.0247	0.0248
A7	0.0255	0.0272	0.0231	0.0254	0.0254	0.0277	0.0281	0.0289
A8	0.0228	0.0256	0.0211	0.0212	0.0212	0.0260	0.0257	0.0260
A9	0.0334	0.0315	0.0290	0.0278	0.0278	0.0349	0.0334	0.0328
A10	0.0200	0.0238	0.0188	0.0190	0.0190	0.0234	0.0234	0.0240

Table 20. Sensitivity Analysis of MARCOS Weights for the Lower Bound

Lower Bound	First & Second	First & Fourth	Second & Fourth	Second & Sixth	Third & Fourth	Third & Fifth	Fourth & Fifth	Fifth & Sixth
A1	0.0227	0.0254	0.0248	0.0258	0.0249	0.0242	0.0242	0.0245
A2	0.0197	0.0198	0.0180	0.0159	0.0217	0.0211	0.0204	0.0200
A3	0.0101	0.0114	0.0108	0.0092	0.0122	0.0110	0.0111	0.0109
A4	0.0098	0.0112	0.0106	0.0090	0.0120	0.0108	0.0109	0.0107
A5	0.0208	0.0194	0.0201	0.0185	0.0188	0.0182	0.0203	0.0201
A6	0.0113	0.0124	0.0121	0.0104	0.0132	0.0127	0.0120	0.0116
A7	0.0156	0.0153	0.0156	0.0184	0.0168	0.0155	0.0157	0.0168
A8	0.0139	0.0158	0.0143	0.0146	0.0166	0.0160	0.0153	0.0155
A9	0.0203	0.0196	0.0192	0.0174	0.0215	0.0222	0.0199	0.0191
A10	0.0139	0.0170	0.0139	0.0139	0.0176	0.0164	0.0165	0.0169

To investigate the effect of changes in the objective weights on the final results, swaps among the weights of the objectives have been performed. In the first change, the objective weights are set as $(Z_1 = 0.5, Z_2 = 0.3, Z_3 = 0.2)$; in the second change, the objective weights are set as $(Z_1 = 0.4, Z_2 = 0.3, Z_3 = 0.3)$; and in the third change, the objective weights are set as $(Z_1 = 0.2, Z_2 = 0.5, Z_3 = 0.3)$.

Table 21. Sensitivity Analysis on the Weights of the Objective Functions

Z3	Z2	Z1	Change
6.2	0.23	79365	First change
6.8	0.28	75211	Second change
6.3	0.37	45222	Third change

Discussion and Conclusion

The findings of the present study demonstrate that the proposed multi-stage decision-making framework—integrating fuzzy MARCOS, cross-efficiency DEA, and a multi-objective mixed-integer mathematical model—provides a robust mechanism for evaluating and selecting project portfolios under uncertainty. The results indicate that the combined use of interval-valued fuzzy assessments and cross-efficiency analysis produces more stable and discriminatory project rankings than single-method approaches. These outcomes align with the growing body of research emphasizing the need for hybrid decision-making methodologies capable of capturing vague, imprecise, and uncertain information inherent in real project environments. Studies in both project portfolio optimization and fuzzy multi-criteria decision frameworks have highlighted that uncertainty-related distortions in criteria weights, performance scores, and efficiency calculations can significantly affect final portfolio decisions (4, 6, 14). The present results reinforce those findings by demonstrating that combining fuzzy modeling with cross-efficiency evaluation reduces the instability of rankings and allows decision-makers to differentiate effectively between similar projects.

The study's results also reveal that the fuzzy MARCOS method successfully captured the relative performance of projects across multiple criteria, including time, cost, ROI, safety, quality, and human resource requirements. MARCOS, particularly in its fuzzy extension, allowed for the integration of best- and worst-case scenarios, contributing to an interval-based ranking reflective of real decision environments. This is consistent with literature indicating that MARCOS performs strongly in environments involving human judgment, linguistic assessments, and data ambiguity (2, 5). The ability of MARCOS to simultaneously compare alternatives to ideal and anti-ideal solutions and generate normalized utility functions makes it particularly suitable for project management contexts, where qualitative and quantitative indicators coexist. Comparable studies in traffic risk assessment and sustainability-driven project evaluation also confirm that fuzzy MARCOS provides stable results even when criteria are highly correlated or conflicting (5, 6). Therefore, the consistency between MARCOS-based rankings in the present study and those reported in previous research demonstrates methodological soundness.

The cross-efficiency DEA stage of the analysis further strengthened the evaluation process by providing a second layer of discrimination among projects. Traditional DEA approaches often suffer from self-evaluation bias, which can inflate efficiency scores and lead to inaccurate benchmarking (9, 10). The cross-efficiency method employed here mitigated that issue by assessing each project not only on its own optimized weights but also on the peer-generated weights across all decision-making units. Previous research shows that such cross-evaluation yields more objective assessments and reduces the frequency of projects being simultaneously rated as fully efficient, which is a typical limitation of standard DEA (7, 16). The results of this study align strongly with those observations, as the cross-efficiency scores displayed greater operational contrast and differentiated more effectively between borderline projects. Furthermore, integrating fuzzy data within DEA matches the recent expansion of DEA in uncertain, imprecise, and interval-based environments, as other researchers have proven that fuzzy DEA models outperform crisp models when project data include ambiguity or subjective indicators (11, 20).

The mathematical programming model formulated in the final stage produced an optimized project portfolio that respects time, cost, workforce, and precedence constraints while maximizing efficiency, MARCOS utility, and overall profitability. This confirms earlier arguments that multi-objective mixed-integer programming is an appropriate tool for handling project interdependencies and resource conflicts in portfolio selection (12, 22). Similar research in NASA, telecommunications, and industrial environments has shown that combining DEA-based efficiency measures with multi-objective optimization enhances portfolio performance, especially when projects compete for limited or shared resources (8, 22). The present findings similarly reveal that efficiency-based prioritization does not always align with profitability-based prioritization, reinforcing past evidence that multi-objective models can uncover nuances that single-objective selection models overlook (13, 15). Thus, the alignment of results with existing literature strengthens the reliability of the modeled decision-making approach.

One of the key insights emerging from the results is the importance of incorporating synergy effects—both cost synergy and revenue synergy—into the portfolio selection process. The present study demonstrated that projects with moderate individual scores may still become optimal selections when synergy effects are taken into account.

This mirrors the findings of portfolio-level interdependence studies, where ignoring interactions between projects may lead to suboptimal or risk-intensive decisions (13, 14). Interdependencies, especially in resource-intensive domains such as construction, information systems, and energy sectors, have been cited as significant contributors to cumulative performance outcomes (9, 17). The results here corroborate that perspective by showing measurable changes in portfolio composition when synergies are modeled explicitly.

The sensitivity analysis conducted in this study adds an important dimension to the interpretation of results. The effect of the defuzzification parameter α on objective functions illustrates that model outputs are sensitive to the risk preferences embedded in the α selection. Comparable studies emphasize that α functions as a behavioral parameter that adjusts optimism or pessimism in decision-making, and its adjustment directly influences portfolio robustness (3, 11). Likewise, the sensitivity of profits to wage costs observed in this study is consistent with project economics literature showing that labor-intensive projects are disproportionately affected by wage volatility (1, 21). The observed sensitivity to budget availability is also in agreement with project finance findings, which state that budget constraints can rapidly shift project priorities and even alter the feasibility of entire portfolios (8, 15). The replication of such behavioral patterns in the present study confirms the model's suitability for real-world conditions.

A meaningful observation in the results relates to the role of skill requirements and workforce training. The model identified that workforce competencies significantly influenced project feasibility and resource scheduling. This observation is consistent with contemporary research emphasizing that human capital factors—skill matching, training requirements, and team dynamics—are increasingly significant determinants of project success in modern project environments (18, 19). Moreover, the interplay between skill distribution and resource allocation fits within broader arguments that workforce constraints can be decisive bottlenecks in large-scale project portfolios (1, 4). The present findings echo these research insights by demonstrating that even highly profitable projects may be excluded from the optimal portfolio if their skill requirements exceed available workforce capabilities.

In summary, the results of this study validate the effectiveness of using a hybrid fuzzy MARCOS–DEA–mathematical modeling framework for project portfolio selection under uncertainty. The alignment between the findings and the existing literature across multiple methodological domains—fuzzy systems, MARCOS, DEA, and multi-objective optimization—demonstrates the validity and relevance of the proposed framework. The model's capacity to integrate uncertainty, synergistic interactions, skill constraints, and resource limitations highlights its suitability for complex decision environments such as construction, telecommunications, energy, and IT project portfolios.

The present study is subject to several limitations. The dataset used for the analysis, while realistic, was limited to a specific context and a restricted number of projects, which may affect generalizability. The fuzzy intervals and linguistic variables were defined based on expert judgment, which, although consistent with common practice, introduces subjective bias into model inputs. Additionally, the model assumes linear or linearized constraints, whereas real-world interactions between projects, resources, and risks may exhibit nonlinear behavior. Computational complexity also increases significantly with the expansion of project numbers, criteria, and synergy relationships, which may limit scalability for extremely large portfolios.

Future research could expand the model by integrating dynamic or stochastic elements to better capture risk fluctuations over time. The model may also be extended by incorporating real options analysis, scenario-based planning, or machine learning mechanisms to enhance predictive accuracy. Cross-industry comparisons could further validate the model's applicability, while developing interactive decision support systems could make the approach more accessible to practitioners. A useful direction would be integrating behavioral decision theory into the weighting process to quantify cognitive biases in expert assessments.

Practical implications of the study are substantial. Project managers can use the integrated framework to make more informed and transparent portfolio decisions, balancing efficiency, profitability, and strategic alignment. Organizations can adopt the sensitivity analysis insights to better prepare for budget changes and labor fluctuations. The identification of skill gaps provides actionable information for workforce planning and training investments, enabling organizations to align human resource development with long-term portfolio strategies.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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