DOI: https://doi.org/10.30525/2256-0742/2026-12-3-216-222

A MULTICRITERIA OPTIMISATION APPROACH FOR INVESTMENT PROJECT FUNDING

Ivan Georgiev[1], Borislav Chakarov[2], Slavi Georgiev[3]

Abstract. This research focuses on the allocation of limited financial resources among competing investment projects using multicriteria methods, with a particular emphasis on funding procedures in which projects are evaluated according to economic, social, environmental and other policy-relevant criteria. In many practical contexts, funding agencies must decide which projects deserve support and how much of the requested budget to allocate to each one when the available budget is insufficient to finance all eligible proposals. The study aims to develop and demonstrate a transparent decision-support model that improves the flexibility and efficiency of financing investment projects by enabling funding decisions to be made on a partial rather than an all-or-nothing basis. The proposed methodology builds on an earlier multicriteria integer linear programming formulation by introducing continuous variables representing the proportion of funding granted to each project, as well as auxiliary binary variables indicating whether a project is approved. The logical relationship between approval and allocation is modelled using Big-M constraints, resulting in a mixed-integer linear programming (MILP) formulation. This model simultaneously maximises the cumulative evaluation scores under each criterion and the number of supported projects while ensuring that the total budget constraint is satisfied. As these objectives may be in conflict with one another, the weighted-sum method is employed to generate Pareto-optimal funding plans. Two procedures for generating weights are considered: systematic iterative stepping over the unit simplex, and quasi-random Sobol-sequence-based generation. To inform the final decision, the global criterion method is used to select the Pareto solution that is closest to the utopian point. The model was implemented in MATLAB using the intlinprog solver and tested on an illustrative dataset comprising eleven investment projects evaluated under three criteria, subject to a fixed total budget. The results show that the partial-funding formulation increases the practical flexibility of the allocation process, offering more options than the original integer-only model. In the binary case, the selected solution may leave part of the budget unused because no additional project can be fully financed. However, the proposed MILP formulation allows the remaining budget to be allocated in fractions, ensuring full utilisation of the budget and enabling support for additional or higher-ranked projects. Computational experiments indicate that this added flexibility does not substantially increase solution time, and may even improve average runtime in the examined setting. The main conclusion is that partial funding provides a more realistic and efficient framework for selecting investment projects under multiple criteria. Nevertheless, the study also shows that unrestricted fractional allocations may result in funding shares that are too small to be meaningful in practice. Therefore, future refinements should include minimum funding thresholds and other policy constraints to ensure that mathematically efficient solutions can be implemented in real financing programmes.

Keywords: investment, funds, projects, multicriteria optimisation, MILP.

JEL Classification: G31, C44, C61

[1] "Angel Kanchev" University of Ruse, Bulgaria;
Institute of Mathematics and Informatics,
Bulgarian Academy of Sciences, Bulgaria
E-mail: irgeorgiev@uni-ruse.bg
ORCID: https://orcid.org/0000-0001-6275-6557
[2] "Angel Kanchev" University of Ruse, Bulgaria;
E-mail: bchakarov@uni-ruse.bg
ORCID: https://orcid.org/0009-0009-7220-9771
[3] "Angel Kanchev" University of Ruse, Bulgaria;
Institute of Mathematics and Informatics,
Bulgarian Academy of Sciences, Bulgaria *(corresponding author)*
E-mail: sggeorgiev@uni-ruse.bg
ORCID: https://orcid.org/0000-0001-9826-9603

1. Introduction

Every investment decision requires an assessment of a project's performance across multiple dimensions, including its economic, social and environmental impacts. Often, these criteria conflict with one another: a project may perform very well in one area but poorly in another. Funding agencies therefore face the recurring dilemma of choosing between fewer projects with higher expected returns and a larger number of projects offering broader societal benefits. As budgets are always limited, it is rarely possible to fund all projects that meet the eligibility requirements.

In order to address this issue, a multicriteria integer linear optimisation model was previously proposed (Raeva & Chakarov, 2024). In that formulation, project funding decisions were binary in nature; a project either received its full requested amount or received no funding at all. The model's objective was to identify the set of Pareto-optimal allocations, with the ultimate decision being left to the experts, who could select from the efficient alternatives based on policy priorities. This approach was shown to be both practical and transparent, but it exhibited a fundamental limitation: the binary restriction reduced flexibility and sometimes left part of the budget unused.

In the present work, the model is extended through the incorporation of partial project funding. The extension has been formulated as a mixed-integer linear programming (MILP) model. The introduction of additional binary variables, in conjunction with the application of the Big-M method, leads to the linearisation of logical constraints, thereby resulting in a convex feasible set. This enables the utilisation of conventional optimisation solvers to identify Pareto-optimal allocations, encompassing projects that are funded both partially and fully.

This contribution makes the decision-making process more realistic, since funding agencies often approve projects for less than the full amount requested in practice. The extended model makes better use of available resources and increases the number of projects that can benefit from financial support. However, it also reveals new difficulties: partial allocations may result in very small funding amounts, which may be insignificant in practice. Therefore, possible extensions to the model are discussed, such as imposing minimum funding level thresholds, to better align mathematical solutions with real-world financing strategies.

This paper is structured as follows: Section 1 introduces the multicriteria investment project funding problem and explains why the approach of granting approvals in the form of all-or-nothing has been replaced by one involving partial allocations. Section 2 presents the multicriteria MILP formulation, including notation, objectives and Big-M logical constraints, and outlines the workflow for generating Pareto-optimal allocations using the weighted-sum method, including Sobol-sequence weight generation. It then explains how to select a balanced plan using the global criterion approach. Section 3 presents the results of numerical experiments that compare the original integer-only model with the partial-funding extension, and discusses the computational aspects of the MATLAB implementation. Section 4 draws conclusions and discusses practical refinements, such as minimum funding thresholds.

2. Mathematical Model with Partial Funding

The decision-making process for the allocation of limited financial resources among competing projects is inherently complex. Each project is evaluated with respect to several criteria, including economic performance, social benefits, and environmental impact. The decision-maker's objective is to achieve the optimal balance across all these dimensions while adhering to the stipulated funding limits.

In the initial formulation (Raeva & Chakarov, 2024), funding decisions were represented by binary variables, whereby each project received either full support or a complete rejection. This all-or-nothing constraint limited the flexibility of the optimisation process. In order to address this issue, the model was extended to allow for partial funding allocations. This resulted in a MILP formulation (Nemhauser & Wolsey, 1999).

The model allocates a limited budget to projects. Each project may receive full, partial or no funding. The optimisation process ensures that the budget is not exceeded while balancing multiple objectives. The outcome is a set of efficient solutions for decision-makers to consider.

2.1 Notation

The definitions of the input data remain the same:

– m – number of projects under consideration.

– m – number of evaluation criteria.

– B – total available budget for project financing.

– b_j – amount requested by the j-th project, $j = 1, \ldots, n$.

– a_{ij} – points assigned to the j-th project under the i-th criterion, $i = 1, \ldots, m$.

Two types of decision variables are now being introduced:

– $x_j \in [0,1]$ – proportion of funding granted to project j.

– $y_j \in \{0,1\}$ – auxiliary binary variable indicating whether project j is funded at all.

The amount allocated to project j is therefore $b_j x_j$.

2.2 Objectives

As before, the model is multi-objective. The first objective is to maximise the cumulative score for each criterion:

$$\max Z_i = \max \sum_{j=1}^{n} a_{ij} x_j, \quad i = 1, \ldots, m.$$

In addition, the objective of maximising the number of approved projects is included:

$$\max Z_{m+1} = \max \sum_{j=1}^{n} y_j .$$

2.3 Constraints

The following conditions must hold:

– Budget constraint – this ensures that the total funding allocated does not exceed the available budget:

$$\sum_{j=1}^{n} b_j x_j \le B.$$

– Logical relation between x_j and y_j – to ensure consistency between partial funding and project approval, the following inequalities are imposed using the Big-M technique (Miettinen, 1999; Williams, 2013):

$$x_j \le M y_j, \quad y_j \le M x_j, \quad j = 1, \ldots, n,$$

where M is a sufficiently large constant ensuring that $y_j = 0$ if $x_j = 0$, and $y_j = 1$ whenever $x_j > 0$.

– Variable domains

$$0 \le x_j \le 1, \quad y_j \in \{0,1\}, \quad j = 1, \ldots, n.$$

2.4 Model formulation

The extended multicriteria MILP can be summarised as follows:

$$\max Z(x, y) = \left[Z_1(x), Z_2(x), \ldots, Z_m(x), Z_{m+1}(y) \right]^T$$

subject to:

$$\sum_{j=1}^{n} b_j x_j \le B,$$

$$x_j \le M y_j, \quad y_j \le M x_j,$$

$$0 \le x_j \le 1, \quad y_j \in \{0,1\}, \quad j = 1, \ldots, n.$$

This formulation converts the integer-only model into a mixed-integer linear problem. The feasible domain becomes convex in the space of continuous variables x_j, which permits the use of standard MILP solvers to explore Pareto-optimal solutions. At the same time, the binary variables y_j preserve the interpretation of project approval, making the extended model both mathematically rigorous and practically meaningful.

2.5 Multicriteria optimisation

The above model defines the following objectives: maximising the cumulative scores under each criterion and maximising the number of funded projects. In practice, however, these objectives conflict with each other.

Generally, there is no single allocation that optimises all objectives at once. Conversely, the objective is to identify a set of Pareto-optimal solutions, which are defined as solutions in which no objective can be improved without worsening at least one other (Miettinen, 1999). This approach provides decision-makers with a balanced set of alternatives rather than a single mathematically dominant outcome.

The weighted sum method is used to convert a multi-objective problem into a single-scalar programme by assigning non-negative weights λ_j to each objective (Zadeh, 1963):

$$Z = \sum_{j=1}^{m+1} \lambda_j Z_j, \quad \lambda_j \ge 0, \quad \sum_{j=1}^{m+1} \lambda_j = 1.$$

Solving the resulting single-objective MILP yields a Pareto-optimal solution. By systematically varying the weights, a set of Pareto-optimal allocations can be generated.

In order to generate these weights, two approaches were investigated. Firstly, stepping through the unit simplex with a predefined increment. Secondly, using a quasi-random Sobol sequence, which is designed to fill the unit simplex more uniformly than purely random sampling (Dick & Pillichshammer, 2010; Bratley & Fox, 1988).

Although the weighted sum method generates a diverse set of Pareto-optimal solutions, ultimately, only one must be chosen for implementation. In order to achieve this objective, the global criterion method is employed. This method minimises the distance between a given point in the criterion space and the points in the feasible set. The chosen point is typically the utopian point (Ehrgott, 2005).

2.6 Visualisation of the approach

Figure 1 displays the workflow of the proposed approach. The process begins with the input of project data, including the number of projects, evaluation criteria and scores, requested amounts, and the total budget. These inputs are incorporated into a mixed-integer linear programming model capable of handling both full and partial funding. The weighted sum method is then applied to convert the multi-objective problem into a single-criterion problem. Solving this problem for different sets of weights generates a collection of Pareto-optimal funding plans that together approximate the Pareto frontier. Finally, the global criterion method identifies the solution that is closest to the utopian point, providing a balanced recommendation that best reconciles competing objectives.

Figure 2 shows how the approach is applied to a three-objective problem. The blue points represent Pareto-optimal solutions, with each point reflecting a different trade-off between the criteria. The red star denotes the utopian point, which corresponds to an ideal but unattainable outcome in which all objectives are maximised simultaneously. The yellow point indicates the Pareto-optimal solution closest to the utopian point. The green line shows the distance between the two points. This illustrates how the method identifies a single balanced solution from across the entire Pareto frontier.

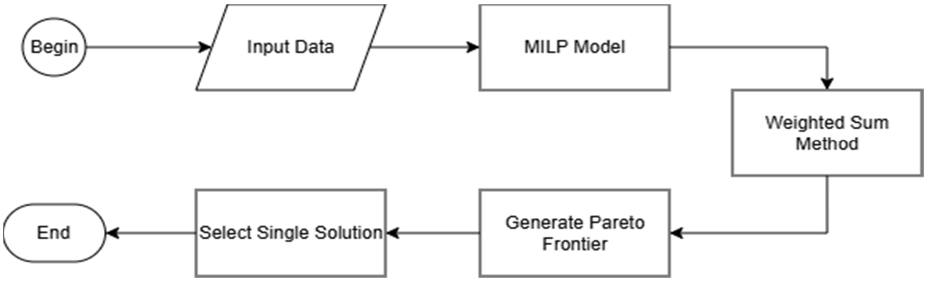

Figure 1. Workflow of the proposed approach

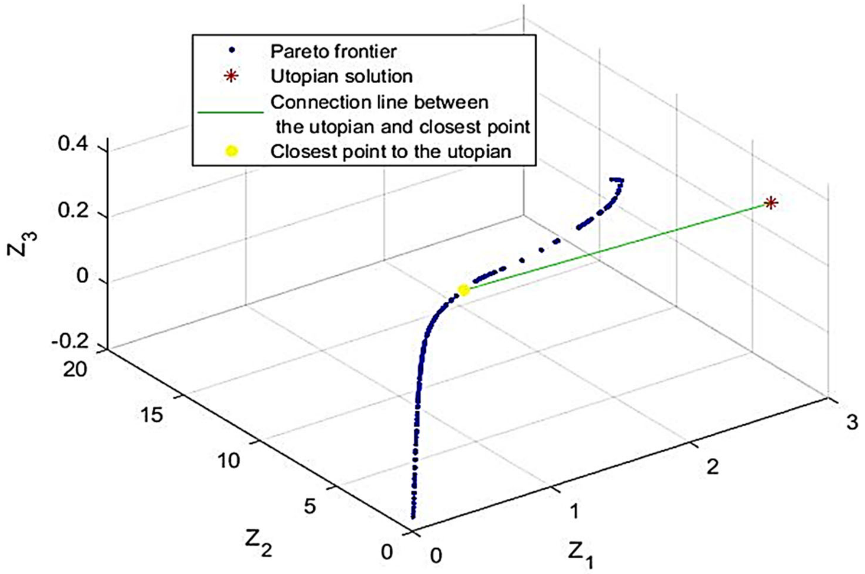

Figure 2. Pareto frontier for the funding problem with three objectives. Blue points represent efficient solutions, the red star marks the utopian point, and the yellow point with the green line illustrates how the final balanced solution is chosen from the frontier

3. Numerical experiments

In order to demonstrate the applicability of the extended model, the same dataset presented in the previous work (Raeva & Chakarov, 2024) is utilised. Eleven projects ($n = 11$) are considered, each evaluated under three criteria ($m = 3$). The normalised scores for each project and criterion, as well as the requested funding amounts, are shown in Table 1. The total budget available for distribution is $B = 259.3$ units.

3.1 Integer-only model

In the original binary model, each project was either fully funded ($x_j = 1$) or not funded ($x_j = 0$). By applying the weighted sum method, 15 distinct Pareto-optimal solutions were obtained.

The optimal solution closest to the utopian point funded seven projects fully ($P_1, P_2, P_3, P_4, P_5, P_7, P_8$). This ensured high overall performance across the three criteria but left some of the budget unused (approximately 1.2 units).

3.2 Partial funding model

The extended MILP formulation now allows projects to receive partial funding.

A representative Pareto-optimal solution is given in Table 2. In this solution, six projects were supported. Project P_{11} received only 25.6% of its requested amount. This partial allocation enabled the full budget to be utilised, which would have been impossible in the integer-only model.

3.3 Comparison

Extending the original integer-only optimisation model to allow partial funding provides a more flexible framework for allocating limited resources among competing investment projects. Numerical experiments have demonstrated the important effects of this modification.

Firstly, the ability to distribute funds in small amounts eliminates the inefficiency of unused budget capacity. In the integer-only model, a portion of the available budget would often remain unallocated because no additional project could be fully funded without exceeding the constraint. In contrast, the partial funding formulation ensures that the total budget is always fully utilised.

Secondly, the new model allows for an increased number of supported projects. While the integer-only

Table 1
Input data for experiments

Project	U_1	U_2	U_3	Requested funding (b_j)
P_1	0.0166	0.6494	0.4233	24.656
P_2	0.2684	0.3189	0.0548	25.810
P_3	0.2861	0.2108	0.4269	30.739
P_4	0.4312	0.2710	0.2959	33.962
P_5	0.4282	0.1517	0.3492	37.275
P_6	0.4541	0.6116	0.5663	47.179
P_7	0.4444	0.7178	0.4283	48.226
P_8	0.8142	0.5997	0.6558	57.409
P_9	0.6394	0.5896	0.5980	62.035
P_{10}	0.8776	0.6896	0.6246	64.634
P_{11}	0.8324	0.7781	0.6527	67.159

Table 2
Pareto optimal solution with partial funding

Project	Given funds (x_j)	Requested funding (b_j)	Given funds (units)
P_1	100%	24.656	24.656
P_6	100%	47.179	47.179
P_7	100%	48.226	48.226
P_8	100%	57.409	57.409
P_{10}	100%	64.634	64.634
P_{11}	25.6%	67.159	17.193

approach selects a fixed set of fully funded projects, partial funding enables additional candidates with lower funding shares to be included. This results in broader support for a more diverse range of project types and, in many cases, improved cumulative scores across the evaluation criteria.

However, the experiments also revealed some drawbacks. Notably, the MILP solutions occasionally allocated very small fractions of funding to certain projects, as low as 0.1% of the requested amount. While these allocations are mathematically valid, they are not practically meaningful for project implementation. From a policy perspective, allocating negligible amounts to numerous projects could diminish the effectiveness of funding programmes.

Therefore, while the partial funding model offers valuable improvements in terms of efficiency and fairness, its practical implementation necessitates further refinements. One promising approach is to introduce minimum funding thresholds to ensure that every supported project receives a sufficient share of its requested budget to make financing viable.

3.4 Computational aspects

Both models were implemented in MATLAB using the intlinprog solver. MATLAB provides a wide range of functions for solving such problems. These include exact algorithms, as well as heuristic, genetic and stochastic algorithms (MathWorks, 2026; Berthold, 2006; Vitliemov, 2004).

Table 3 summarises the average computational times.

Table 3
Average computational time (seconds)

Method for generating weights	Integer model	Partial funding model
Iterative weights	13.23	9.32
Sobol sequence	12.01	8.56

The results show that the partial funding model did not introduce any significant additional computational overhead, and in fact reduced the average runtime thanks to improved solver convergence properties.

3.4 Results and discussion

Numerical experiments confirm that the proposed partial-funding MILP formulation modifies the structure of the investment allocation problem in a meaningful way from a practical perspective. In the original integer-only model, projects could be approved or rejected in full. Consequently, even a balanced solution selected from the Pareto-optimal set may result in part of the available budget being left unused, as the remaining amount is insufficient to finance another project in full. In the presented experiment, the integer-only model generated 15 distinct Pareto-optimal solutions, and the solution closest to the utopian point fully financed seven projects, namely P_1, P_2, P_3, P_4, P_5, P_7, and P_8. However, this allocation left approximately 1.2 budget units unused.

This limitation is eliminated by the partial-funding formulation, which allows the remaining budget to be allocated in fractions. In the representative Pareto-optimal solution reported in Table 2, five projects, P_1, P_6, P_7, P_8, and P_{10}, were fully funded, while project P_{11} received 25.6% of its requested amount. This result shows that the proposed model can use the full budget and include an additional high-scoring project by providing partial support. Therefore, the research's main practical outcome is an increase in mathematical flexibility and the ability to construct funding plans that more closely resemble real-world decision-making situations, where reduced or partial financing is often preferable to complete rejection.

The comparison also shows that partial funding affects the trade-off between the number of projects that are supported and the quality of those projects. The integer-only solution selected a greater number of projects in full, whereas the partial-funding solution allocated resources to a different set of projects and used fractional allocation to avoid budget loss. This confirms that the proposed model does not simply mechanically maximise the number of funded projects, but rather enables the decision-maker to explore alternative combinations of project quality, coverage and budget utilisation that are Pareto-optimal. In this sense, the model provides a richer framework for supporting decisions than the original binary formulation.

The computational results further support the applicability of the proposed approach. Although the partial-funding model introduces additional continuous and binary variables, the average solution time remained unchanged. In fact, in the experiments conducted, the partial-funding model achieved lower average computational times: 9.32 seconds compared to 13.23 seconds for iterative weight generation and 8.56 seconds compared to 12.01 seconds when Sobol-sequence weights were used. This suggests that the model's additional practical flexibility can be achieved without a significant computational cost for problems of this size.

At the same time, the experiments revealed an important limitation. Since the current formulation permits any positive funding proportion, some Pareto-optimal solutions may allocate very small amounts of funding to selected projects. While such allocations are mathematically feasible, they may be unsuitable for real-world financing schemes, where projects usually require a minimum level of support to be implemented. This result suggests that the proposed model should be interpreted as a flexible baseline formulation. For practical applications, it can be extended by introducing minimum funding thresholds, sectoral priorities, eligibility rules or other policy constraints. The numerical results therefore demonstrate the advantages of partial funding and the need for further refinement when adapting the model o real funding programmes.

4. Conclusions

This study presented an extension to this authors' previous multicriteria optimisation model for project financing. The original formulation was based on binary decision variables, which resulted in funding allocations being restricted to an all-or-nothing choice. In the current study, partial funding was introduced by reformulating the problem as a mixed-integer linear programme. By using auxiliary binary variables and the Big-M technique, the consistency between partial allocations and project approval was ensured, while the ability to search for Pareto-optimal solutions was preserved.

The numerical experiment showed that, unlike the integer-only formulation, the proposed partial-funding model achieves full utilisation of the available budget. In the selected balanced solution, approximately 1.2 budget units remained unused. The partial-funding solution also enabled the inclusion of project P_{11} with 25.6% of its requested amount, showing how fractional allocation can transform an otherwise infeasible full-funding decision into a feasible partial-support decision. Further computational comparisons showed that the extended MILP formulation did not increase the average solution time for the given example.

The extended model offers several advantages, including more efficient use of the total budget, greater flexibility in supporting a larger number of projects and improved opportunities to balance multiple evaluation criteria. However, the results also highlight new challenges. For example, partial allocations may be unrealistically small, raising questions about the practical feasibility of such solutions. To address this issue, future research should focus on refining the model by incorporating constraints that enforce minimum funding proportions. This would bring the mathematical solutions into closer alignment with the real-world decision-making practices of funding agencies (Keeney & Raiffa, 1993).

In summary, the proposed partial funding model is a significant step forward in developing decision support tools for evaluating investment projects. It broadens the range of possible solutions, improves the utilisation of resources, creates new opportunities for balancing competing objectives and opens avenues for further methodological refinement.

Acknowledgements

This study was supported by the European Union – NextGenerationEU, through the National Recovery and Resilience Plan of the Republic of Bulgaria, project No. BG-RRP-2.013-0001.

References:

Raeva, I., & Chakarov, B. (2024). Multicriteria optimization approach for investment project financing evaluation and decision making. *Springer Proceedings in Mathematics & Statistics*, vol 488, Springer, Cham. https://doi.org/10.1007/978-3-031-83398-4_30

Nemhauser, G. L., & Wolsey, L. A. (1999). *Integer and Combinatorial Optimization*. New York: Wiley-Interscience.

Miettinen, K. (1999). *Nonlinear Multiobjective Optimization*. Boston, MA: Kluwer Academic Publishers.

Williams, H. P. (2013). *Model Building in Mathematical Programming* (5th ed.). Chichester: Wiley.

Ehrgott, M. (2005). *Multicriteria Optimization* (2nd ed.). Berlin: Springer.

Zadeh, L. A. (1963). Optimality and non-scalar-valued performance criteria. *IEEE Transactions on Automatic Control*, 8, 59–60. https://doi.org/10.1109/TAC.1963.1105511

Dick, J., & Pillichshammer, F. (2010). *Digital Nets and Sequences: Discrepancy Theory and Quasi-Monte Carlo Integration*. Cambridge: Cambridge University Press.

Bratley, P., & Fox, B. L. (1988). Algorithm 659: implementing Sobol's quasirandom sequence. *ACM Transactions on Mathematical Software*, 14(1), 88–100.

MathWorks. (2026). *Mixed Integer Linear Programming Solver*. Available at: https://www.mathworks.com/help/optim/ug/intlinprog.html

Berthold, T. (2006). *Primal Heuristics for Mixed Integer Programs*. Berlin: Technische Universität Berlin.

Vitliemov, V. (2004). *Optimization Methods* (2nd ed.). Ruse: University of Ruse.

Keeney, R. L., & Raiffa, H. (1993). *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. Cambridge: Cambridge University Press.

Received on: 11th of March, 2026
Accepted on: 15th of May, 2026
Published on: 03rd of July, 2026