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Dynamic Project Portfolio Optimization with Portfolio Stability and Switching Costs: A Multi-Period MILP Approach

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Abstract
Project portfolio optimization entails the process of choosing projects to obtain maximum portfolio value subject to budget, resource, and selection restrictions. In multi-period scenarios, there are decision interdependencies, and changes in projects' inclusion give rise to termination, resourcing, coordinating, contractual, and organizational adjustments, which should be taken into account to avoid high-value portfolios with too much project switching. In this paper, a dynamic MILP approach is proposed, where project portfolio stability is achieved via project-switching costs between periods. Transition binary variables denote changes between periods, while the objective function maximizes portfolio value and accounts for project transitions, giving the possibility to investigate the trade-off between economic value and portfolio stability. The model is tested on 30 artificial instances with 250 projects in three periods, choosing 50 projects per period subject to budget and resource restrictions. Sensitivity analysis is carried out for $\lambda = 0$, 1, 2, and 3. It has been found that $\lambda = 2$ reduces project switching by 57.0% with 0.208% portfolio value loss, and $\lambda = 3$ reduces project switching by 73.1% with 0.375% portfolio value loss.

Keywords: Project portfolio optimization; dynamic portfolio selection; mixed-integer linear programming; portfolio stability; switching costs; multi-period optimization; computational experiment.

1. Introduction

1.1 Background and Motivation

There is always competition for limited financial and human resources within an organization. Project Portfolio Management is used to guide the process of project evaluation and selection, taking into account budget, resources, strategy, and sustainability. Recent research work has applied mixed integer and multi-criteria optimization models to solve such issues (Tavana et al., 2020; Ma et al., 2020; Hoseini et al., 2020).

1.2 Project Portfolio Optimization in Dynamic Environments

Portfolios in multi-period environments are still linked over time, with projects being altered, postponed, or substituted, causing re-allocation of resources, financial considerations, learning effects, and coordination challenges. The literature focuses on dynamic synergy and portfolio management (Bai et al., 2022; Shen & Li, 2023; Qiu et al., 2024; Shen et al., 2025), but binary switch costs are not well-studied yet.

1.3 Limitations of Value-Oriented Portfolio Selection

The goal of the value maximization approach is to maximize the value of projects, within budgetary constraints and available resources, but it does not consider the impact of changes in the selection of projects that will change from one period to another. Such changes could lead to switching costs such as resource transfer, coordination, termination, and implementation.

1.4 Research Problem

The following work incorporates the idea of switching variables in the MILP formulation in order to connect decisions between subsequent periods.

1.5 Research Questions

RQ1: Does a switching cost decrease portfolio instability?

RQ2: What is the impact of portfolio stability on portfolio value?

RQ3: Is the value-stability trade-off valid for large-scale problems?

1.6 Contributions of the Study

Inter-period switching costs are developed and analyzed in the context of dynamic project portfolio optimization.

1. Dynamic linking: Links portfolio decisions over consecutive periods.
2. Explicit switching: Incorporates binary variables for portfolio changes.
3. Value–stability trade-off: Maximizes the value of the portfolio with switching penalties.
4. Large-scale analysis: Analyzes 30 problems with 250 candidate projects.
5. Trade-off measure: Analyzes value, switching, lost value, stability improvement, variability, and solution time.

2. Literature Review

2.1 Project Portfolio Optimization

More recent studies concerning portfolio management have shifted their focus from simple ranking of projects to comprehensive optimization approaches dealing with resource restrictions, uncertainty, sustainability, project dependencies, and scheduling. Tavana et al. (2020) introduced a two-stage uncertain model, while Ma et al. (2020) included sustainability considerations. Hoseini et al. (2020) paid attention to resource-constrained multi-objective selection problems, while Arratia-Martinez et al. (2021) developed an integrated approach for selection, scheduling, resource allocation, and divisibility of projects by means of MILP. Hamidi Hesarsorkh et al. (2021) dealt with R&D portfolio selection under uncertainty, while Kettunen and Lejeune (2022) presented decision-dependent stochastic models. Zorluoğlu and Kabak (2022) solved multi-objective selection and scheduling, and Harrison et al. (2022) studied multi

The dynamism of portfolio decisions in planning periods is another issue that recent literature focuses on. The literature by Bai et al. (2022) and Shen and Li (2023) discussed dynamic synergies and dynamic project synergies, respectively. Portfolio risks with interdependent projects were the focus of the research conducted by Bai et al. (2023), while the relationship between projects was studied by Bai et al. (2024). Project life cycles and interactions were considered by Qiu et al. (2024), while risk correlation, interruption, and scheduling effects were analyzed by Saiz et al. (2024). Robustness of portfolio adjustment under capability uncertainty during implementation was discussed by Shen et al. (2025), while net present value and delayed delivery were examined by Li et al. (2025).

2.2 Research Gap

The studies under review tackle issues related to multi-period selection, uncertainty, and adjustments of the portfolio but lack a specific modeling framework for the cost of switching that is binary in nature and involves changes in the membership status of projects across multiple periods (Kettunen & Lejeune, 2022; Shen & Li, 2023; Qiu et al., 2024; Shen et al., 2025).

3. Proposed Dynamic Portfolio Optimization Model

3.1 Problem Definition and Framework

This methodological model represents DPPPO-PSC as a Multi-Period Mixed-Integer Linear Programming Problem (MILP). In each of the periods, projects are chosen based on budget limits, resource capacity limits, and a fixed portfolio size. Contrary to a project selection process that takes place individually for each period, in the proposed model, there is an association between the decision-making processes for each period. Each alteration made to the selection process results in a switching cost. Figure 1 demonstrates this methodology.

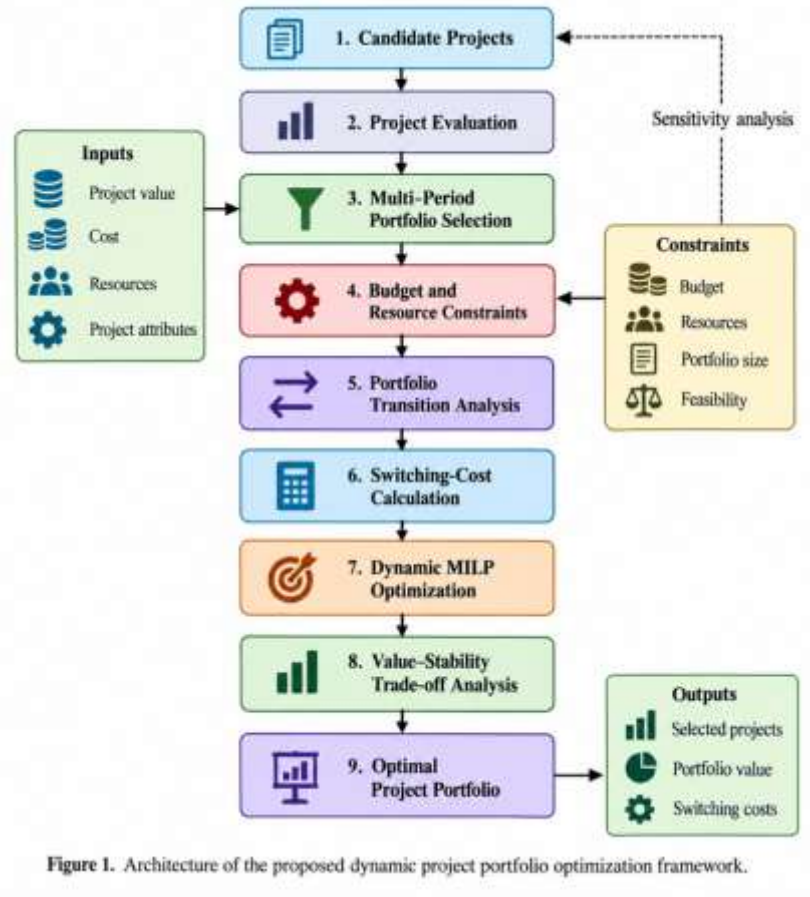


Figure 1. Architecture of the proposed dynamic project portfolio optimization framework.

The model takes into account the N number of candidate projects during T number of planning horizons. V_{it} represents the value of project i at period t, while C_i and R_i represent its cost and resource, respectively. Budget and resource capacity for each period can be denoted by B and K, respectively. The number of projects per period is always constant at P. The switching penalty is represented by λ.

3.2 Mathematical Formulation

Define x_{it} as a binary decision variable, which equals 1 if project i is chosen in period t, and 0 otherwise. In order to model changes in the portfolio over successive periods, define the binary decision variable z_{it} as a transition variable for $t = 2, \dots, T$. The decision variable z_{it} equals 1 if the selection status of project i changes over consecutive periods $t-1$ and t.

The value of the total portfolio is formulated by the expression:

$$PV = \sum_{i=1}^{N} \sum_{t=1}^{T} V_{it}\, x_{it}$$

The switching events are modeled using the following set of linearization constraints:

$$z_{it} \geq x_{it} - x_{i,t-1}$$
$$z_{it} \geq x_{i,t-1} - x_{it}$$

These constraints express the absolute value of the difference between two consecutive binary selections of the portfolio. As the objective function is maximization, z_{it} equals 1 when the selection status of a project switches. The number of switching activities is

$$S = \sum_{i=1}^{N} \sum_{t=2}^{T} z_{it}$$

while the corresponding switching penalty cost is λS. In the objective function, both the portfolio value and stability are optimized together:

$$\max \sum_{i=1}^{N} \sum_{t=1}^{T} V_{it}\, x_{it} - \lambda \sum_{i=1}^{N} \sum_{t=2}^{T} z_{it}$$

The problem formulation involves the following budget constraints:

$$\sum_{i=1}^{N} C_i\, x_{it} \leq B,\ \forall t$$

and a resource-capacity constraint:

$$\sum_{i=1}^{N} R_i\, x_{it} \leq K,\ \forall t$$

The fixed portfolio-size requirement is given by

$$\sum_{i=1}^{N} x_{it} = P,\ \forall t$$

with binary restrictions

$$x_{it}, z_{it} \in \{0, 1\}$$

The above mentioned relationship forms the entire MILP problem formulation. This linear program can be solved using standard techniques for finding the global optimum solution. If λ=0, there will be no switching cost in the problem, giving only the benchmark value.

3.3 Computational Evaluation

The model being proposed is subjected to analysis through a synthetic controlled computational experiment. The experimental setting involves the use of a benchmark that consists of 250 potential projects divided into three periods, with 50 projects chosen per period. There are 1000 budgets for the 300 resources allowed per period. The cost of the projects varies from 10 to 30, while the resource requirement varies from 2 to 8. The value of each project is generated based on its quality score with the period-dependent variance.

Four cases of the switching penalty are considered: $\lambda = 0$, $\lambda = 1$, $\lambda = 2$, and $\lambda = 3$. The project dataset and feasibility constraints remain the same for all four cases to ensure that the results do not depend on the changes in the input instances.

There are 30 independent synthetic experiments to be conducted. Every single experiment is to be done for each individual λ, keeping note of the portfolio value, switching, switching reductions, portfolio value lost, and computing time. There is a static master random seed used for reproducibility purposes, along with storing the data generated and the computation results. This experiment is to be used as a proof-of-concept in a synthetic fashion and not an empirical one.

4. Computational Experimental Design

4.1 Experimental Objectives and Synthetic Project Generation

The purpose of this computational experiment is to see whether a switching penalty can lower portfolio instability without compromising the portfolio's value. A value maximization model acts as a baseline and is followed by progressively stability-oriented models. In the value-maximizing model λ is 0, whereas for the model proposed in this paper λ is 1, 2, and 3. The same project data and feasibility constraints are used in all three scenarios to study the impact of the switching penalty.

Since the portfolio data of organizations could not be obtained for this research, synthetic project data will be created. Each project has cost, resource requirement, value, and quality attributes to define its period-specific value. Cost lies between 10 and 30 units, and resource requirement lies between 2 and 8 units. The quality attribute, in combination with period-specific values, helps to create different values of projects per period. The same data instances are used for all penalty scenarios.

Every test case involves 250 candidate projects through three planning horizons. Such a number of candidates is consistent with current findings on problems of project selection with constraints of resource availability and scheduling (Harrison et al., 2022; Hosseinian &Esmaeeli, 2024). The following values for $\lambda = 0,1,2,3$ will create two inter-horizon transitions between adjacent planning horizons.

4.2 Experimental Settings and Switching-Penalty Scenarios

Table 1 depicts the main experimental environments. All cases include 250 project candidates, three planning periods, and fixed project selections of 50 for each period. The values for budget and resource capacity are 1,000 and 300, respectively. Thirty cases are analyzed through the MILP model.

Table 1. Experimental Settings

Parameter	**Experimental Setting**
Candidate projects	250
Planning periods	3
Projects selected per period	50
Budget per period	1,000
Resource capacity per period	300
Number of independent instances	30
Switching penalties	0, 1, 2, 3
Optimization approach	MILP

As presented in Table 1 below, all four experiments have the same portfolio constraints except for the switching penalty coefficient, which differs in each case. S_0, where $\lambda = 0$, is the value-only model while S_1, where $\lambda = 1$, indicates a small switching penalty, S_2, where $\lambda = 2$, depicts an intermediate switching penalty and S_3, where $\lambda = 3$, is a larger switching penalty. The goal here is not to find an optimal value for λ but rather to show how different organizational attitudes toward portfolio stability affect project selection.Table 2 presents the switching-penalty scenarios used in the experiment.

Table 2. Switching-Penalty Scenarios

Scenario	λ	**Interpretation**
S0	0	Value-only benchmark
S1	1	Low switching penalty
S2	2	Moderate switching penalty
S3	3	Higher switching penalty

Portfolio value (PV), project switches (S), portfolio value loss compared to benchmark, switching reduction, and computational time are computed for each case. Portfolio value is computed as

$$PV = \sum_{i} \sum_{t} V_{it}\, x_{it}.$$

The number of switches is determined by

$$S = \sum_{i} \sum_{t=2}^{T} | x_{it} - x_{i,t-1} |.$$

Portfolio-value loss relative to the value-only benchmark is calculated as

$$Loss(\%) = \frac{PV_0 - PV_\lambda}{PV_0} \times 100,$$

while switching reduction is calculated as

$$Reduction(\%) = \frac{S_0 - S_\lambda}{S_0} \times 100.$$

Solver execution time is also recorded for every optimization run to assess computational feasibility.

4.3 Reproducibility and Computational Procedure

The algorithm will produce 250 project candidates, along with the cost and resource requirements and value of each project in each period. The MILP for three periods will be solved for $\lambda = 0, 1, 2, and\ 3$, using the same instance of the project. Portfolios' value, switching events, and performance metrics will be collected for 30 different runs. Mean, standard deviation, minimum, and maximum will be computed in order to analyze the value-stability relationship. The same random seed will ensure replicability, while project data and outputs will be kept for future reference. This study is a conceptual demonstration, not an empirical validation.

5. Computational Results and Discussion

5.1 Overview of Computational Results

The proposed dynamic project portfolio optimization model was then verified with 30 independent synthetic instances, where each instance consisted of 250 projects within three planning horizons, with 50 projects being selected in each horizon. The experiments were run in order to compare value maximization.($\lambda = 0$) to the stability-aware models with $\lambda = 1,2,$ and 3. The aim was to investigate whether the penalty for changing projects could stabilize the portfolio and influence its overall value. Results of the aggregation of all 30 instances are shown in Table 3.

Table 3. Aggregate Computational Results for the 250-Project Portfolio

λ	Mean Portfolio Value	Mean Switches	Mean Value Loss (%)	Mean Switch Reduction (%)
0	14,472.40	60.13	0.000	0.0
1	14,462.86	39.67	0.066	34.2
2	14,442.27	25.73	0.208	57.0
3	14,418.08	15.93	0.375	73.1

As observed from the findings, there is a negative correlation between the switching penalty and the number of project transitions. The higher the value of λ, the more weight the model gives to portfolio continuity and the lower its likelihood of switching project allocations. Hence, the value of the portfolio gradually falls as the model is willing to sacrifice some portfolio value for greater stability. In essence, the results have provided computational proof that a switching cost model enhances portfolio stability without losing too much portfolio value.

5.2 Effect of Switching Penalties on Portfolio Stability

The first research question tested the ability of an explicit switching penalty to minimize portfolio instability. Given that $\lambda = 0$, the value-only benchmark generated 60.13 portfolio switches on average. Increasing λ to one caused a drop in portfolio switches to 39.67, which was a reduction of 34.2%. An increase in λ to two caused a decrease in portfolio switches to 25.73, which was a reduction of 57.0%. When $\lambda = 3$, portfolio switches were 15.93, which is a 73.1% reduction.

Table 4. Stability Improvement Relative to the Value-Only Benchmark

Switching penalty	Mean switches	Reduction from benchmark
0	60.13	0.0%
1	39.67	34.2%
2	25.73	57.0%
3	15.93	73.1%

The findings indicate a clear downward trend for portfolio switches with increasing.λ values. This is consistent with the structure of the model, since each additional transition is subject to a penalty. The drop is significant, with the value of 2 for λ reducing over half of all the switching in the benchmark on average. This can be seen from Figure 2 below, which depicts the effect of λ on mean project switches for 30 cases.

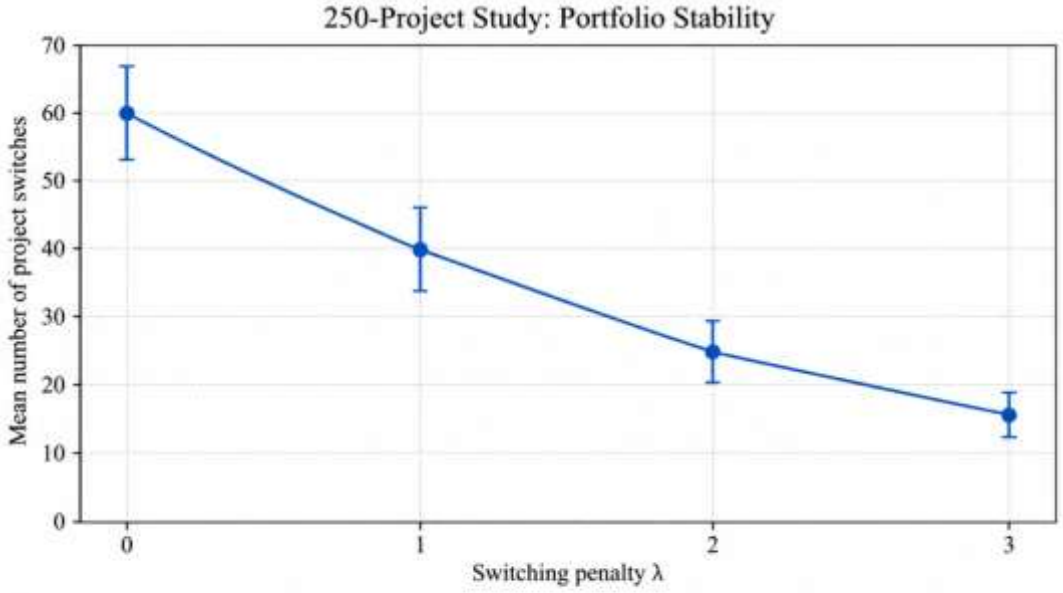


Figure 2. Relationship between Switching Penalty λ and Mean Number of Project Switches Across the 30 Instances.

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5.3 Effect on Portfolio Economic Value

The second research question pertains to the cost involved in making the portfolio stable economically. The value-only benchmark gave an average portfolio value of 14,472.40. After introducing $\lambda = 1$, the average value fell slightly to 14,462.86, implying a 0.066% decrease in average value. For $\lambda = 2$, the average portfolio value fell to 14,442.27, which means that there was a decrease in average value of 0.208%. For $\lambda = 3$the average value fell to 14,418.08, which means there was a 0.375% decrease in the average value. Table 5 gives the economic impact of portfolio stabilization.

Table 5. Economic Effect of Portfolio Stabilization

λ	Mean Portfolio Value	Mean Value Loss (%)
0	14,472.40	0.000
1	14,462.86	0.066
2	14,442.27	0.208
3	14,418.08	0.375

The decline in the value of the portfolio is significantly lower than the decline in the switching of the portfolio. The case of $\lambda = 2$, for instance, decreases the switching rate by 57.0%, but the decline in the portfolio-value loss is just 0.208%. Likewise, the case of $\lambda = 3$ reduces switching by 73.1%, but the portfolio-value loss stays below one-half of one percent. The mean portfolio-value loss in each case is depicted in Figure 3.

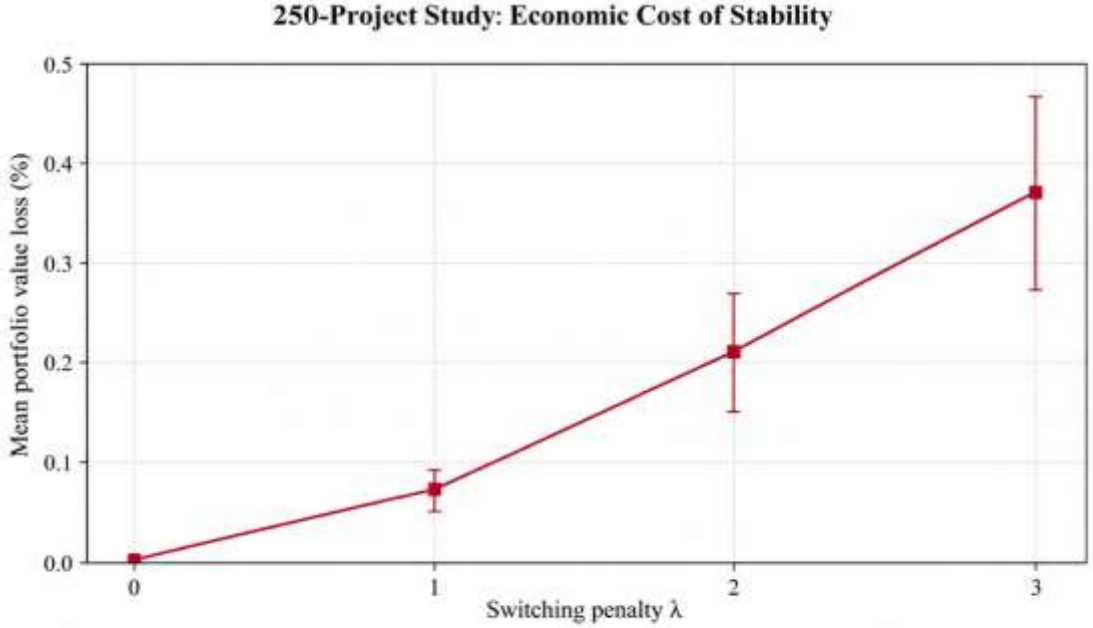


Figure 3. Mean Portfolio-Value Loss (%) as a Function of the Switching Penalty λ.

Figure 3. Mean Portfolio-Value Loss (%) as a Function of the Switching Penalty λ.

This result is significant since it shows that achieving the stability goal does not always entail sacrificing the portfolio's value by much. The optimization process was successful in substituting higher-valued yet unstable combinations for combinations that have a lower value but are significantly more stable across periods.

5.4 Value–Stability Trade-off

The critical result is that of the compromise between the value of the portfolio and its stability. The value-maximizing approach makes changes easier in terms of projects, while introducing switching costs increases stability.

- $\lambda = 0$: maximum value and highest switching.
- $\lambda = 1$: moderate stability improvement with very small value loss.
- $\lambda = 2$: substantial stability improvement with limited value loss.
- $\lambda = 3$: very large stability improvement with a somewhat larger, but still relatively small, value reduction.

These findings demonstrate that there is no single answer to the problem, as the model provides several different combinations of the portfolio. The penalty for the switch may be an indicator of the organization's concern with continuity based on its business conditions. Therefore, λ is an indicator of the economic preference for stability of the portfolio. The value-stability trade-off curve is provided in Fig. 4.

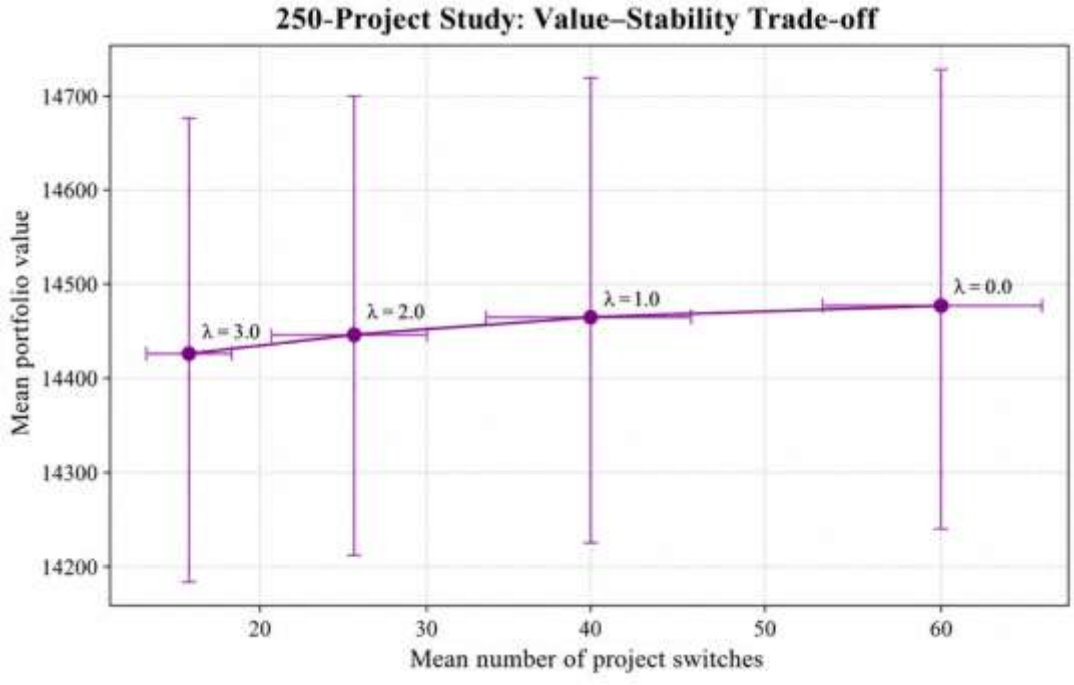


Figure 4. Mean Portfolio Value Against Mean Number of Project Switches Across λ = 0, 1, 2, 3, Illustrating the Value–Stability Frontier.

According to the computational results, the value of the first effect may be significantly higher than the value of the second effect in the given range of parameters.

5.5 Cross-Instance Consistency

The use of random data may give rise to the suspicion that any results seen are particular to specific cases rather than the algorithm. In order to increase consistency, the experiment was performed with 30 independent instances of 250 projects. The same set of project data was used for all instances across all λ conditions; switching penalties were applied independently.

Table 6. Paired Comparison Across the 30 Instances

λ	Mean Switch Reduction	Mean Value Loss	Instances with ≥50% Switch Reduction	Instances with <1% Value Loss
1	34.2%	0.066%	—	30/30
2	57.0%	0.208%	27/30	30/30
3	73.1%	0.375%	30/30	30/30

In case $\lambda = 2$, 27 out of 30 problems managed to have a 50% or higher switching decrease, and all problems had a portfolio-value decrease of less than 1%. In case $\lambda = 3$all 30 problems had a 50% or higher switching decrease and a portfolio-value decrease of less than 1%. The results confirm that the stability effect is consistent with independent portfolio scenarios. However, because of the fact that the data used were artificial and the probability distribution was assumed, one cannot use percentages as predictors for real-life companies.

5.6 Computational Performance

The proposed formulation was computationally tractable for the 250 projects' case studies. The formulation relies on binary variables for project-period decisions and also binary variables for period transitions. Despite the relatively large size of the project set, all case studies were solved quickly by the computer. Table 7 presents the computational results.

Table 7. Computational Performance

λ	Approximate Mean Solution Time

0	0.044 s
1	0.088 s
2	0.102 s
3	0.078 s

The results reveal that the introduction of switching variables does not lead to significant computational difficulties with regard to the 250 project case under consideration. Nonetheless, the interpretation of the results should be made cautiously since the analysis is conducted using three planning periods and relatively easy conditions of budgets and resource allocation, project selection, etc. It is possible that a greater number of projects, more complex constraints, etc., will make the computations more difficult.

5.7 Interpretation of the Switching Penalty

The variable λ is pivotal in the suggested method and has to be interpreted cautiously. In the ongoing computational experiment, λ is a sensitivity parameter under control rather than an organizational cost value that is estimated directly. Thus, $\lambda = 1$, $\lambda = 2$, and $\lambda = 3$ cannot be viewed as universal monetary values.

For implementation purposes, the switching penalty can be represented via costs of project transitions:

$$C_{it}^{\text{switch}} = C_{it}^{\text{termination}} + C_{it}^{\text{reallocation}} + C_{it}^{\text{coordination}} + C_{it}^{\text{transition}}$$

The objective can then be extended to:

$$\max\left[\sum_i \sum_t V_{it} \cdot x_{it} - \sum_i \sum_{t=2}^{T} C_{it}^{\text{switch}} \cdot z_{it}\right]$$

Transition costs for project-specific tasks will allow us to provide a better economic meaning of the model rather than the use of a universal cost for all tasks. Some specialized tasks may require more switching costs compared to small projects that have common tasks. The current experiment should be considered as an initial sensitivity analysis, whereas in the future it will be possible to measure transition costs in different ways.

5.8 Managerial Implications

A number of practical implications arise from these results for project portfolio managers. Portfolio selection should be recognized as interlinked over time, as modifications to previous selections influence future choices. Portfolio stability may be considered an observable economic variable, where switching variables reflect project turnover. Instead of only selecting between maximum value and perfect stability, portfolio managers can investigate intermediate approaches. In the experiment, setting $\lambda = 2$ caused a 57.0% decrease in average switching with a mere 0.208% drop in mean portfolio value. This approach allows one to find various points on the value-stability trade-off curve. Furthermore, organizational awareness regarding financial and operational impacts of project modifications can be taken into account when calculating switching costs.

5.9 Discussion of Research Questions

RQ1: Does a switching cost decrease portfolio instability?

Yes. When the penalty was increased from 0 to 3, the mean switching went down from 60.13 to 15.93, a 73.1% decrease.

RQ2: What is the impact of portfolio stability on portfolio value?

More stability entails a slight decrease in the value of the portfolio. For $\lambda = 2$there is a decrease of 57.0% in switching, but only 0.208% in the portfolio value.

RQ3: Is the value-stability trade-off valid for large-scale problems?

Stability will result in a slight drop in portfolio value. For $\lambda = 2$switching will drop by 57.0%, while the portfolio value will drop only by 0.208%.

5.10 Limitations of the Computational Results

Some aspects that need to be taken into account include: First, the use of artificial data for modeling purposes. This does not fully represent reality since portfolios in organizations might vary in terms of their characteristics. Second, the switching penalty is set in a uniform way for all projects in question, although in reality the costs might be different for each case. Third, the number of periods is limited and equals three. However, for more complex cases, there could be more periods, and this would complicate both the strategy and the computation. Fourth, the model considers only some aspects of portfolio management such as portfolio value, budget, resources, and switching and ignores risk, uncertainty, dependencies, precedence, strategic fit, or even managerial capabilities.

5.11 Overall Discussion

Computational evidence suggests the plausibility of the conjecture that increasing the switching cost term will stabilize a multi-period portfolio at the expense of a minor decline in its value. The $\lambda = 2$ case exhibits a reduction in switching by 57.0% but only loses 0.208% of the mean portfolio value, whereas the $\lambda = 3$ case shows a reduction in switching by 73.1%, with the mean portfolio value decreasing by just 0.375%. These results show that stability can be increased while not harming the portfolio performance too much. However, the right value of the penalty will depend on the actual cost of changing the projects in the economy. Thus, the model is meant to allow organizations to assess the impact of the portfolio instability rather than suggest the optimal penalty.

6. Conclusions and Future Research

This study presents a dynamic MILP model for multi-period project portfolio selection including switching costs across periods via binary variables. In 30 independent cases comprising 250 projects in three periods, the increase in switching penalty increased portfolio stability by 73.1% at $\lambda = 3$ while decreasing portfolio value by 0.375%. The model combines portfolio stability with resource-constrained multi-period project portfolio selection and contributes to the literature on the dynamic adjustment and interactions of projects (Shen & Li, 2023; Qiu et al., 2024; Shen et al., 2025). It assists decision-making in analyzingtrade-offs between portfolio value and stability through adjustable switching penalties and project-dependent transition costs. Nevertheless, the study relies on synthetic data, one type of penalty, a three-period horizon, and overlooks risk, interdependence, precedence, and strategic alignment. Future studies must consider project-dependent costs, risk using stochastic and robust approaches (Hamidi Hesarsorkh et al., 2021; Kettunen & Lejeune, 2022; Bazargan et al., 2026; Han et al., 2026), real organizational data, multi-objective optimization (Zorluoğlu& Kabak, 2022; Li et al., 2025), and longer horizons with interdependence and risk propagation (Bai et al., 2023; Han et al., 2026).

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