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Computer-Supported Strategic Decision Making for Ecosystems Creation

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Abstract: In the corporate strategy arena, the concept of ecosystems has emerged as a transformative approach to promote competitive advantage, growth, and innovation. Corporate ecosystems enable companies to benefit from interconnections among diverse partners, products, and services to deliver enhanced value to customers. However, the process of ecosystem creation represents a significant challenge for CEOs, as they must analyze a wide number of alternative sectors, partners, business cases, and other critical elements. Particularly, as it is a strategic decision, it lies beyond the traditional approach of risk-return by incorporating other factors, e.g.: the feasibility, desirability and sustainability of each alternative. This paper investigates how computer-supported optimization algorithms can help to solve the complex problem faced by CEOs when making these factors to create a successful and sustainable ecosystem. The paper shows how a CEO can make informed strategic decisions by identifying the best projects to include in the ecosystem portfolio, balancing financial risk and return with technical feasibility, customer appeal, and technical considerations.

Keywords: strategic decision making; corporate ecosystems; computers in industry; optimization algorithms

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1. Introduction

Corporate ecosystems refer to networks of organizations—including businesses, suppliers, customers, competitors, and other stakeholders—that collaborate and interact within a shared environment to achieve common goals or create value [1]. Becoming a relevant player in such a corporate ecosystem is one of the top priorities of the next CEO agenda [2]. Among the various strategies to achieve corporate growth, CEOs seek to bring a more complete offer to their customers that evolve from pure industry players to an integral value proposition by encouraging different forms of collaboration with companies of different industries. In this ecosystem context, CEOs face the constant challenge of allocating their limited resources efficiently to a portfolio of strategic projects that reinforces the competitive advantage of the company and supports a sustainable and profitable growth. The CEO's decision on which projects to invest in is considered strategic, as it will significantly impact the organization's success in the medium and long term [3]. Knowing how to tackle this strategic decision implies that CEOs understand the portfolio optimization problem (POP) [4–6], where they will select the project that meets the strategic objectives from a wide range of candidate projects.

In traditional portfolio optimization, the goal is either to maximize the returns for a given level of risk or minimize the risk for a given level of returns. In the rich version of the POP that models ecosystem construction, other strategic metrics need to be considered

Menold et al. [7]. As Urli and Terrien [8] elaborated in their paper, objectives and constraints can be of quantitative nature (such as return or risk), or pertain to qualitative measures (such as the desirability for the customer or the feasibility of the solution). In the dynamic and interconnected environment of corporate strategy, CEOs must consider a variety of both quantitative and qualitative factors that influence long-term sustainability and alignment with the company's overarching goals [9]. The classical Markowitz model focuses primarily on minimizing risk while keeping the expected return above a user-defined threshold [10]. While the expected return, as financial viability, remains a crucial aspect, the decision-making process of creating a corporate ecosystem demands a broader consideration of factors to ensure alignment with the company's vision and long-term strategy [11,12]. Drawing insights from various researches, we present a structured overview of the main factors that guide CEOs in this strategic decision. Key focal points include customer perception as well as feasibility alignment with sustainability objectives. A visual example of corporate ecosystems factors is represented in Figure 1.

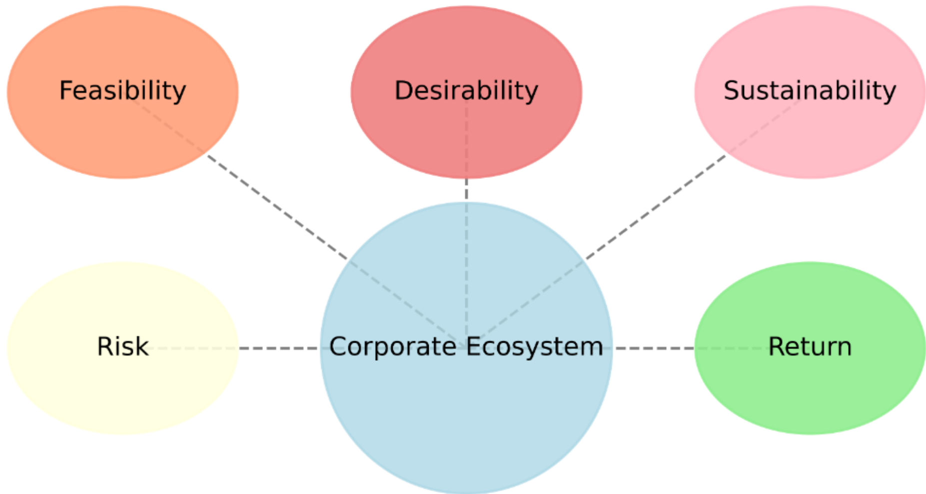

Figure 1. Corporate Ecosystems Factors.

In particular, we have considered four key factors related to the creation of a corporate ecosystem according to [7,13]:

- Viability (V) is the financial return. It is generally measured as the expected net present value of cash flows or the percentage of return according to the investment amount. Milhomem and Dantas [14] provide an overview of current developments in methodologies for the project portfolio selection problem (PPSP) to measure risk-return performance.
- Desirability (D) measures how attractive a project or partnership is to potential customers or stakeholders. Several authors are working on measuring this factor, e.g., Lopez and Castillo [15], Barnum and Palmer [16] and Benedek and Miner [17].
- Feasibility (F) is the technical consideration of the solution, assessing whether the ecosystem can realistically be implemented given the current technological, logistical, and expertise-related resources. Feasibility requires aligning technological capabilities with strategic objectives, considering logistical constraints, and evaluating the compatibility of potential partnerships or technologies. Menold et al. [7] elaborates on the importance of measuring feasibility, especially in supply chain management.
- Sustainability (S) encompasses the economical, environmental and social dimensions (including ethical and governance aspects). Sustainability ensures that the ecosystem adheres to corporate social responsibility standards and aligns with long-term environmental and social goals. This factor is increasingly crucial in strategic decision making due to growing regulatory pressures and stakeholder expectations about sustainable practices. This is a hot topic where Haessler [18] and Chernev and Blair [19] sets

the importance of considering environmental, social, and governance factors of the corporate sustainability strategy.

Hence, the main goals of this paper are: (i) to map the major factors of CEOs when making strategic decisions for the creation of ecosystems; (ii) to explore the benefits of computer-supported optimization algorithms for creating ecosystems; (iii) to analyze the results of a case study regarding the application of such algorithms to support decision making; and (iv) to determine limitations and future areas of study regarding the implementation of these algorithms in strategic decisions on creating ecosystems. The remaining of the paper is structured as follows: Section 2 presents a review of the literature to investigate and synthesize studies on the creation of ecosystems and the use of computer-supported algorithms in decision-making processes. Section 3 contains the mathematical formulation of the problem. Section 4 explains the solution approach. Then, the computational experiments and their associated results are presented in Section 5. Lastly, we present our main findings and further research lines in Section 6.

2. Related Work

This section focuses on achieving insights from the scientific community regarding the major factors influencing CEOs' strategic decision making in the creation of corporate ecosystems alongside an exploration of the current state of artificial intelligence (AI) in strategic decision-making processes, particularly focusing on the PPSP and POP. To achieve this, an exhaustive search strategy was implemented, including publications from Elsevier, Google Scholar, Scopus and Web of Science. Keywords such as: 'CEO decision making on corporate ecosystems', 'ecosystem creation', 'strategic decision-making processes', 'measurement of feasibility, desirability and sustainability in strategic projects', 'project portfolio selection problem', and 'multi-objective portfolio optimisation' were employed. To ensure currency and relevance, we restricted the period to the last five years (from 2019 to 2023). As a result, 123 publications were initially identified, comprising 10 book chapters, 26 conference proceedings, and 87 articles. Following a rigorous screening process, 47 papers were selected based on their alignment with the objectives of this study.

2.1. CEOs Deciding the Creation of Ecosystems

Strategic decision making in ecosystem creation requires significant investment in resources and affects long-term profitability and survival of the firm. As defined by Adner [20], Vera et al. [21] and Shepherd and Rudd [22], this process encompasses a series of rational, comprehensive, and political tasks, including information gathering, alternative creation, and selection. While much of the existing literature provides a qualitative review of ecosystem strategies, focusing on the rationale behind CEOs' shift towards ecosystem models, our analysis extends deeper into both theoretical and empirical dimensions. Discussions around ecosystems have often been based on Markowitz portfolio theory, emphasizing the optimal balance of return and risk. However, Adner and Kapoor [23], Adner [24] has shifted the focus toward how ecosystems can create collective value beyond mere profitability, enhancing product depth and customer complementarities. Scholars like Clarysse et al. [25], Jacobides et al. [26], and Wei et al. [27] further detail the mechanics of ecosystem construction, examining strategic decisions that emphasize the importance of high-quality partnerships and selective promotion strategies. Talmar et al. [28] introduced the Ecosystem Pie Model (EPM), which helps to visualize the ecosystem's components including value propositions, user segments, and the roles of various actors and resources. Furthermore, Rodriguez-Garcia et al. [29] have mapped the integration of AI and the internet of things (IoT) into these strategic processes, pinpointing a gap in understanding the evolutionary dynamics of ecosystems, including partner networks, internal capabilities, and governance structures.

The literature also covers strategic portfolio matrices, like the Boston Consulting Group Matrix and the GE Matrix of McKinsey, which serve as tools for analyzing and selecting business strategies based on market position and industry attractiveness. Discussions around non-financial factors such as desirability, particularly concerning user experience, are found in works by Griffin [30] and Adikari et al. [31]. Menold et al. [7] and Najmi and Makui [32] take a look at the feasibility aspects, considering internal business processes and the environment, highlighting the importance of flexibility, reliability, and responsiveness in ecosystem management. Sustainability has become a significant focus, integrating environmental and social governance into strategic frameworks as discussed by Husted and Allen [33] and Kuhlman and Farrington [34]. This shift towards sustainability is reflected in modern strategic decisions, incorporating principles of the triple bottom line and corporate social responsibility to ensure ecosystems are not only profitable, but also ethically and environmentally sound. This enriched understanding of ecosystem creation underscores the complexity of CEO decision making in today's business environment, where strategic agility and comprehensive analysis are relevant.

2.2. AI in Strategic Decision Making for Ecosystems

The strategic application of AI in ecosystem management, particularly through the PPSP and POP, is a rapidly evolving field with extensive literature exploring its complexities Trunk et al. [35], Adesina et al. [36] . The methodologies for these problems are generally categorized into two main types: standard methods, which include tools like multi-criteria decision trees and the analytical hierarchy process, and advanced quantitative methods. These sophisticated approaches are designed to address the difficulties of multi-objective decision making in complex environments. For example, Mehrez and Sinuany-Stern [37] described PPSP as a search for utility functions that encapsulate various organizational goals. Rao [38] utilized goal programming in conjunction with a DELPHI process to map decision-maker preferences, highlighting the effort required to align strategic objectives with practical outcomes. The introduction of decision support systems like PROSEL by Rădulescu and Rădulescu [6] further aimed to improve the quality of the selection of the project portfolio.

Innovations continued with the analytic network process [39] and the strategic portfolio management tool [40], which incorporate complex analytical models to refine decision-making processes. Techniques such as fuzzy logic [41] and mathematical programming models [42] integrate stochastic elements and simulations to manage complexity effectively. Recent developments have seen the rise of simheuristic algorithms, as discussed by Chica et al. [43]. These algorithms combine metaheuristics with simulation techniques, allowing decision makers to handle uncertainties and achieve high-quality solutions in unpredictable environments. Metaheuristics, as described by Glover and Kochenberger [44], provide feasible solutions within acceptable time frames for complex problems, demonstrating their utility in strategic ecosystem management. Applications of metaheuristics in finance are considered in and Doering et al. [45]. This diverse array of models and methods underscores a significant trend towards integrating more intricate, data-driven approaches to optimize ecosystem creation and management, reflecting a shift towards more adaptive, robust strategic planning tools that cater to the dynamic needs of modern businesses.

2.3. Gaps on the Application of AI in Strategic Decision Making

Despite the scientific literature identifies and utilizes various strategic decision models and tools for ecosystem creation, significant gaps remain. Advances in AI for strategic decision making in ecosystem creation could be applied with particular models and visualizations. The EPM, inspired by Ron Adner's work [20], highlights the need for decision models that dynamically adapt to changing market conditions, regulatory changes, and technological disruptions. Furthermore, existing AI applications lack comprehensive metrics to accurately measure the effectiveness of ecosystem strategies and often fail to account for complex interdependencies [46]. Additionally, the complexity of AI tools poses barriers for non-technical decision makers, suggesting a need for more user-friendly designs to make AI more accessible [47]. Simplifying user interfaces and improving the interpretability of AI outputs are essential steps toward making advanced AI tools more accessible and actionable for strategic decision making.

Based on the reviewed literature, Table 1 highlights the contribution of our article and how our approach differs from previous related papers.

Table 1. Comparative Analysis of References and Contributions.

Reference	Focus on Financial Metrics (Risk-Return)	Includes Strategic Ecosystem Factors	Dynamic Decision Models	Incorporates AI Usability	Empirical Validation	Integration of ESG Factors	Broader Strategic Alignment
Yang and Yan [1]	Yes	Yes	No	No	No	Yes	Yes
Autio [2]	Yes	Yes	Yes	No	No	No	Yes
Buehring and Bishop [3]	Yes	Yes	Yes	No	No	No	Yes
He et al. [4]	Yes	No	Yes	Yes	No	No	No
Loke et al. [5]	No	No	Yes	Yes	No	No	No
Sumar and Karlsson [9]	Yes	Yes	Yes	No	Yes	No	Yes
Markowitz [10]	Yes	No	No	No	No	No	No
Adner [20], Adner and Kapoor [23]	No	Yes	Yes	No	No	No	Yes
Jacobides et al. [26]	No	Yes	No	No	No	No	Yes
Wei et al. [27]	No	Yes	Yes	No	No	No	No
Milhomem and Dantas [14]	Yes	No	No	No	No	No	No
Trunk et al. [35]	No	Yes	Yes	Yes	No	No	No
Adesina et al. [36]	No	Yes	Yes	Yes	No	No	No
Danesh and Ryan [40]	No	Yes	Yes	Yes	No	No	Yes
Talmar et al. [28]	No	Yes	Yes	Yes	No	No	No
This paper	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Foundational studies, such as the work of Markowitz [10], primarily address financial metrics like risk and return without considering broader strategic factors. Adner [20], Adner and Kapoor [23], Autio [2] and Jacobides et al. [26] emphasize ecosystem creation but focus on viability and desirability, overlooking feasibility and sustainability as critical dimensions. Similarly, He et al. [4] as well as Milhomem and Dantas [14] explore financial viability but do not integrate qualitative factors or ESG considerations. In contrast, Yang and Yan [1] and Kuhlman and Farrington [34] delve into sustainability, but their work does not incorporate quantitative optimization or ecosystem-specific dynamics. The contributions of Urli and Terrien [8], West et al. [12] and Adesina et al. [36] emphasize AI-driven optimization and dynamic decision models, yet they lack practical insights into usability for non-technical decision-makers and fail to align these tools with strategic corporate goals.

3. Mathematical Model

The CEOs problem described above can be modeled as a rich POP, where CEOs are optimizing for conflicting objectives (risk minimization and return maximization), while aiming certain levels of desirability, feasibility, and sustainability. Consider a set of n projects, $P = \{1, 2, \ldots, n\}$. For each project $i \in P$, CEOs must decide how much to invest in it, denoted by x_i, which represents the percentage of the total available budget invested in project i. The investment can range from 0% (no investment) to 100% of the budget, i.e., $x_i \in [0, 1]$ for all $i \in P$. The objective is to minimize the risk of the portfolio, which includes only the projects with a positive investment. A binary variable, $z_i \in \{0, 1\}$, takes the value 1 if project i has been selected by the CEO to be included in the portfolio, and 0 otherwise. The risk is measured in terms of the covariance matrix of the project investments. Additionally, the expected returns of the selected projects must exceed a given threshold $R > 0$. The problem also considers the following constraints:

- Desirability constraint: The desirability level of the portfolio must meet a predefined threshold, $D > 0$.
- Sustainability constraint: The sustainability level of the portfolio must meet a specific threshold, $S > 0$.
- Technical feasibility constraint: The portfolio must meet a certain technical feasibility level, $T > 0$.
- Budget constraint: The total percentage of the budget invested across all projects should not exceed the available budget.
- Portfolio size constraint: The number of projects in the portfolio must be within user-defined limits, $n_{\min}$ and $n_{\max}$.
- Minimum/maximum investment constraints: If project i is included in the portfolio, a minimum investment $l_i > 0$ must be made, and at most a maximum investment $u_i \geq l_i$ is allowed.

Let σ_{ij} represent the covariance between projects i and j for all $i, j \in P$. Additionally, for each project $i \in P$, let $r_i > 0$ denote the expected return, $d_i > 0$ the desirability value, $s_i > 0$ the sustainability value, and $t_i > 0$ the technical feasibility value. The rich version of the POP to minimize risk can be formulated as follows:

$$\text{Minimize:} \quad \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \sigma_{ij} \quad \text{(minimize risk)} \tag{1}$$

Subject to:

$$\sum_{i=1}^{n} x_i r_i \geq R \quad \text{(return constraint)} \tag{2}$$

$$\sum_{i=1}^{n} d_i x_i \geq D \quad \text{(desirability constraint)} \tag{3}$$

$$\sum_{i=1}^{n} s_i x_i \geq S \quad \text{(sustainability constraint)} \tag{4}$$

$$\sum_{i=1}^{n} t_i x_i \geq T \quad \text{(technical feasibility constraint)} \tag{5}$$

$$\sum_{i=1}^{n} x_i \leq 1 \quad \text{(budget constraint)} \tag{6}$$

$$n_{\min} \leq \sum_{i=1}^{n} z_i \leq n_{\max} \quad \text{(portfolio size constraint)} \tag{7}$$

$$l_i z_i \leq x_i \leq u_i z_i \quad \forall i \in P \quad \text{(minimum/maximum investment constraint)} \tag{8}$$

$$z_i \in \{0, 1\} \quad \forall i \in P \quad \text{(binary decision variables for project selection)} \tag{9}$$

$$x_i \geq 0 \quad \forall i \in P \quad \text{(non-negativity constraint)} \tag{10}$$

The solution to the problem will be presented using a Pareto frontier, where each curve represents the risk-return combination of projects for a given set of values associated with the desirability, sustainability, and technical feasibility constraints. At each point on the frontier, there is a precise allocation of projects, along with their specific investment percentages. One of the key contributions of our paper is that it allows CEOs to understand the impact of improving one objective at the expense of another. This enables the quantification of trade-offs, showing the cost in terms of risk and return when incorporating a more desirable, sustainable, or feasible project into the portfolio of projects for constructing the ecosystem.

4. Solving Approach

The mathematical model proposed in the previous section is a mixed-integer quadratic programming problem. It can be solved with exact optimization algorithms, which are available in different commercial and open source software. In our case, we have modeled the problem using Pyomo, a Python-based and open-source optimization modeling language (https://www.pyomo.org/, accessed on 3 December 2024). Once modeled, we have solved it using the Gurobi optimization engine (https://www.gurobi.com/, accessed on 3 December 2024).

The process begins by initializing the problem parameters required for the optimization problem, such as desirability, technical feasibility, and sustainability thresholds (Listing 1).

Listing 1. Define problem parameters.

```python
from pyomo.environ import ConcreteModel, RangeSet, Var, NonNegativeReals, Objective,
    minimize
from pyomo.environ import Expression, Constraint, Binary, SolverFactory, value, Param
import numpy as np

# Define parameters
n_min = 1
n_max = num_assets
min_xi = 0.0
max_xi = 1.0
big_M = 1e20

des_threshold = 0.0  # desirability threshold
fea_threshold = 0.0  # technical feasibility threshold
sus_threshold = 0.0  # sustainability threshold
np.random.seed(42)  # set the seed to a specific value for reproducibility
a = 7  # each asset level is random between a and b
b = 10  # b > a
des_levels = a + (b - a) * np.random.rand(num_assets)
fea_levels = a + (b - a) * np.random.rand(num_assets)
sus_levels = a + (b - a) * np.random.rand(num_assets)
```

Subsequently, we generate the optimization model using Pyomo v6.8.2., defining the objective function and the constraints (Listing 2).

Listing 2. Objective function and constraints.

```
# Generate the Pyomo−Gurobi model
model = ConcreteModel()  # define the Pyomo model
model.I = RangeSet(1, num_assets)  # define set of indexes
model.x = Var(model.I, domain=NonNegativeReals)  # define variables

# Define the objective function

 def portf_risk_rule(model):
    p_risk = sum(sum(cov_matrix[i−1][j−1] * model.x[i] * model.x[j] for j in model.I) for i in model.I)
    return p_risk

# Expressions to compute portfolio objectives
model.portf_risk = Objective(rule=portf_risk_rule, sense=minimize)
model.portf_return = Expression(expr=sum(avg_returns[i−1] * model.x[i] for i in model.I))
model.portf_des = Expression(expr=sum(des_levels[i−1] * model.x[i] for i in model.I))
model.portf_fea = Expression(expr=sum(fea_levels[i−1] * model.x[i] for i in model.I))
model.portf_sus = Expression(expr=sum(sus_levels[i−1] * model.x[i] for i in model.I))

# Budget contraint
model.sum_weights_cons = Constraint(expr = sum(model.x[i] for i in model.I) <= 1.0)

# Return threshold constraint
model.return_threshold = Param(initialize=0.0, mutable=True)
model.return_cons = Constraint(expr = model.portf_return >= model.return_threshold)

# Positive weights constraint
model.low_weight_cons = Constraint(model.I, rule=lambda model, i: model.x[i] >= 0)

# Portfolio desirability level constraint
model.des_cons = Constraint(expr = model.portf_des >= des_threshold)

# Portfolio technical feasibility level constraint
model.fea_cons = Constraint(expr = model.portf_fea >= fea_threshold)

# Portfolio sustainability level constraint
model.sus_cons = Constraint(expr = model.portf_sus >= sus_threshold)

# Cardinality constraints
model.is_asset_selected = Var(model.I, within=Binary)
for i in model.I: # initialize the binary variable
    model.is_asset_selected[i] = 0

def is_asset_selected_rule_1(model, i): # if x[i] > 0 then is_asset_selected[i] == 1
    return model.x[i] <= model.is_asset_selected[i]
model.is_asset_selected_cons_1 = Constraint(model.I, rule=is_asset_selected_rule_1)

def is_asset_selected_rule_2(model, i): # if x[i] == 0 then is_asset_selected[i] == 0
    return model.is_asset_selected[i] <= model.x[i] * big_M
model.is_asset_selected_cons_2 = Constraint(model.I, rule=is_asset_selected_rule_2)

def count_selected_assets_rule(model):
    return sum(model.is_asset_selected[i] for i in model.I)
model.num_selected_assets = Expression(rule=count_selected_assets_rule)
model.portf_size_lb_cons = Constraint(expr = model.num_selected_assets >= n_min)
model.portf_size_ub_cons = Constraint(expr = model.num_selected_assets <= n_max)

# Minimum and maximum investment constraints
model.up_weight_cons = Constraint(model.I, rule=lambda model, i: model.x[i] <= max_xi)

def selected_asset_min_invest_rule(model, i):
    return model.x[i] >= min_xi * model.is_asset_selected[i]
model.selected_asset_min_invest_cons = Constraint(model.I, rule=selected_asset_min_invest_rule)
```

Finally, we choose Gurobi 12.0 as the optimization solver and use it to find the optimal solution for each return threshold (Listing 3).

Once the algorithm finalizes, the results are printed and visualized in a Pareto graph. The code prints a Pareto curve containing 2000 points. Each point contains the optimal portfolio allocation for a given configuration of parameters.

Listing 3. Solve the optimization problem.

```
# Choose a solver engine
solver = SolverFactory('gurobi')

# Construct the Pareto frontier
results = []

k = 0
for threshold in return_thresholds:
    k = k + 1

    # Reset selected assets from the model
    for i in model.I: # reset all is_asset_selected to 0
        model.is_asset_selected[i] = 0
    model.return_threshold = threshold # update the return threshold parameter

    # Find optimal portfolio for defined return threshold
    solver.solve(model)

    # Extract the solution information
    opt_weights = [round(value(model.x[i]), 4) for i in model.I]
    risk = round(value(model.portf_risk()), 6)
    exp_return = round(value(model.portf_return), 6)
    des = round(value(model.portf_des), 1)
    fea = round(value(model.portf_fea), 1)
    sus = round(value(model.portf_sus), 1)
    n_selected = value(model.num_selected_assets)

    # Save solution information in dictionary
    results.append({'Return': exp_return, 'Risk': risk, 'Desirab': des, 'Feasib': fea,
                    'Sustainab': sus, 'N selected': n_selected, 'Weights': opt_weights})
```

5. Computational Experiments and Results

The proposed Pyomo-Gurobi algorithm is executed in Python. We use a standard personal computer, manufactured by ASUSTeK COMPUTER INC. in Taipei (Taiwan), with an Intel Core *i*7 CPU at 2.5 GHz and 12 GB RAM with Windows 10 to run all tests.

5.1. Creation of the Database for the Experiment

In order to validate the correctness and effectiveness of our algorithm we have used a realistic database, which is described in Chang et al. [48] for the risk-return variables. These authors constructed five test data sets considering the stocks involved in five different capital market indices drawn from around the world. Specifically, he considered Hang Seng (Hong Kong), DAX 100 (Germany), FTSE 100 (UK) and S&P 100 (USA). The indices have been extensively used in computational experiments by scholars within the related body of research Tasgetiren and Suganthan [49] and Lu and Vasko [50]. The data were sourced from Datastream to obtain weekly price data for the stocks in these indices with a time frame from March 1992 to September 1997. The data cleaning process was run to eliminate stocks with missing values from the analysis. Return is calculated as the average of 52 periods, each of which covers one week, covering a period of 5.5 years. This approach smooths out erratic fluctuations and provides a solid perspective on company returns. Risk is measured through standard deviation, making it possible to identify variability in investment returns. With the data of returns and risk we have calculated the respective covariance matrix. As a result, there were 291 values available for each stock to compute returns and covariances. The datasets varied in size, ranging from 31 to 225 stocks. All the test problems are publicly available from OR-Library (https://people.brunel.ac.uk/~mastjjb/jeb/info.html, accessed on 19 October 2024).

Due to the fact that there is no public and objective information on the desirability, feasibility and sustainability factors, we have decided to use a random creation of these variables. The values will be generated with the NumPy 2.1 library of Python. The establishment of corresponding thresholds will be a discretion of the user (CEOs). In this paper we use 3 different thresholds for each variable and for the 5 indices.

5.2. Analysis of Results

Figures 2–5 show the results after applying our approach to the four datasets of the different capital markets. The results are shown in a curve that encapsulates the Pareto-optimal solutions derived from the optimization process, considering the delicate equilibrium between risk and return within the specified ecosystem. The Pareto curve is formed by 2000 points, each point on the curve signifies a distinct project portfolio with specific weights assigned to individual projects. In each graph there are four Pareto curves, one just considering the risk-return and the other three reflecting the application of constraints for the different threshold's' values of desirability, feasibility and sustainability. In practice, this means that the Pareto's curves provide a visual representation of the trade-off in terms of risk-return when adding the different constraints. Note that the algorithm displays the surface map associated with tri-dimensional Pareto curves, where the first axis representing risk, the second axis representing return and the third axis is the combination of different values of desirability, feasibility and sustainability. Notably, the third axis, representing the confluence of strategic factors, introduces a layer of complexity in the decision-making process, as it transcends the conventional risk-return paradigm. The figures demonstrates that as the level of desirability increases (the ability of the portfolio to meet strategic objectives), the algorithm recommends portfolios with slightly higher risk but significantly improved return. This illustrates that the inclusion of desirability as a constraint shifts the balance towards higher-yielding portfolios, even though the associated risk also rises.

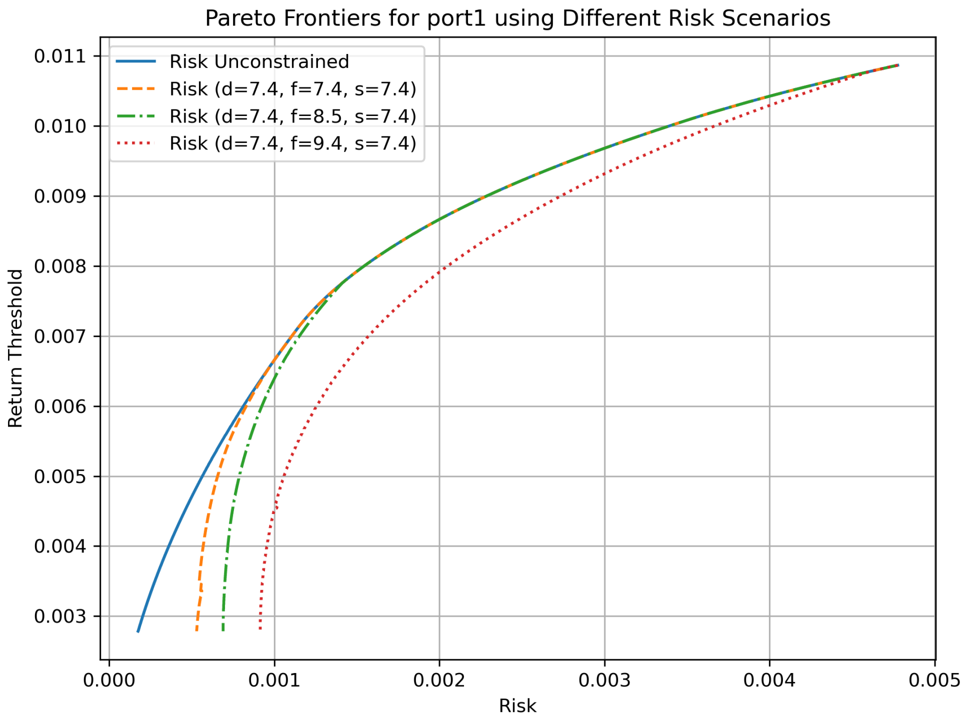

Figure 2. Experiment 1.

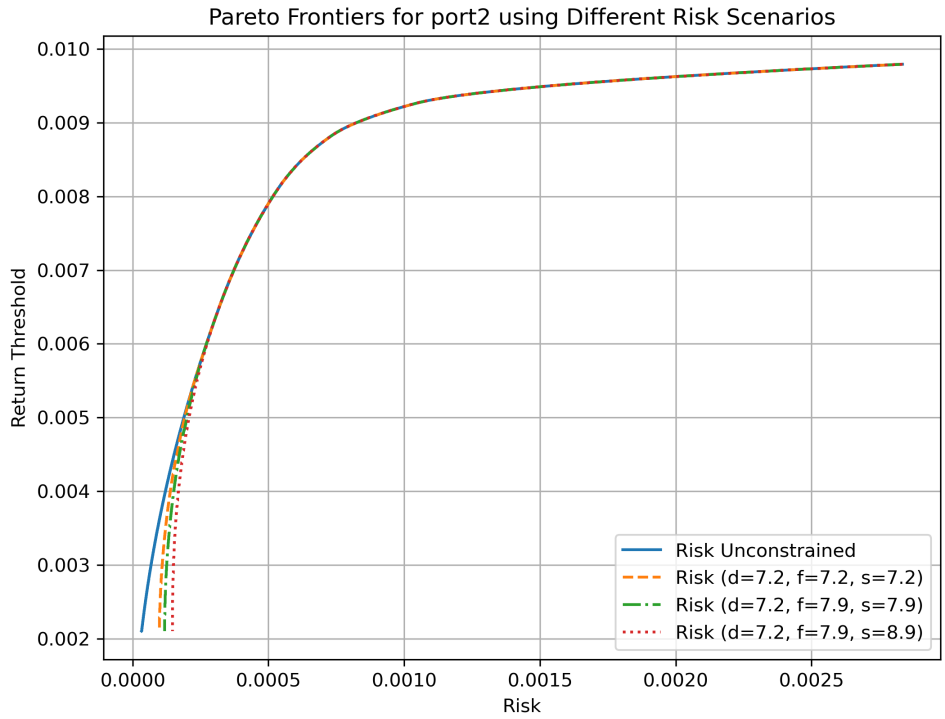

Figure 3. Experiment 2.

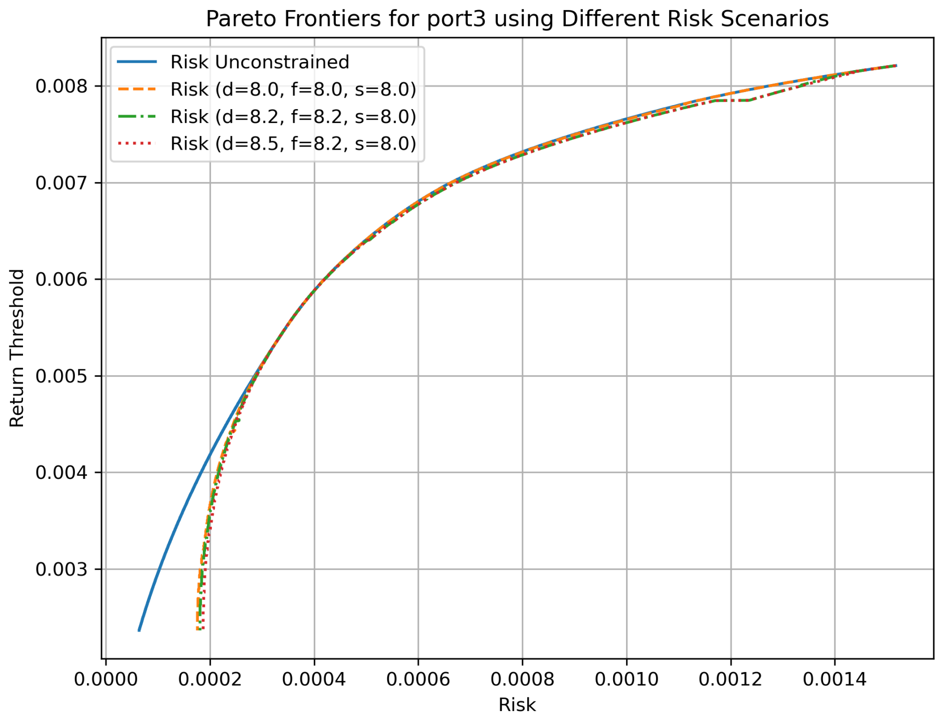

Figure 4. Experiment 3.

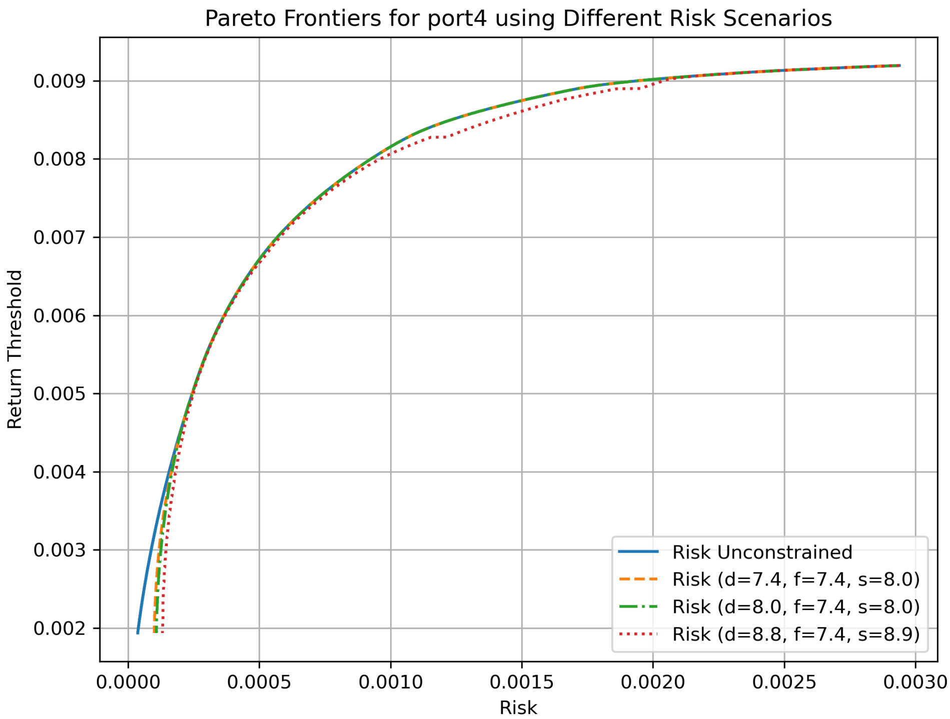

Figure 5. Experiment 4.

The initial analysis focuses on the calculation of the efficient frontier just considering the approach of risk-return (unconstrained). The goal is to determine the efficient project allocation as if it was a financial portfolio, without considering the strategic factors. As a CEO, this is a starting point to understand the maximum potential returns available in the ecosystem portfolio and the associated risks. The unconstrained Pareto curve serves as a baseline depiction of the inherent dynamics between risk and return within the ecosystem. This curve, meticulously crafted from 2000 points, encapsulates the spectrum of achievable optimal solutions. The curvature of this curve delineates the unfettered interplay between risk mitigation and return enhancement, offering decision makers an unobstructed view of the landscape of possibilities. Moreover, to test the effectiveness of our algorithm, we first used them to find the unconstrained efficient frontier. Adopting this approach has the advantage that the curve can be exactly calculated by the algorithm and the results can be compared with the optimal benchmark solutions provided by Chang et al. [48]. Figure 3 shows that as risk tolerance increased, the algorithm selected higher-risk, higher-return projects. Low risk tolerance resulted in more diversified portfolios while high risk tolerance led to more concentrated portfolios with potentially higher returns.

The second analysis focuses on the impact of incorporating strategic factors—desirability, feasibility, and sustainability—on risk-return. The goal is to introduce a new variable to the strategic-decision process and to quantify how increasing these factors can lead to a reduction in the total reward collected. The constrained Pareto curve manifests itself as a result of the algorithm's operation under the influence of strategic constraints: desirability, feasibility, and sustainability thresholds act as guiding principles, shaping the curvature of the Pareto frontier. This constrained curve, intricately woven with the same 2000 points, reflects the trade-offs introduced by strategic considerations. The curvature of the surface indicates the non-linear relationship between these three constraints, emphasizing that decision makers must carefully balance these factors when selecting optimal ecosystem portfolios.

From Figure 4 we observe a negative correlation between sustainability and return: as the sustainability constraint tightens, the portfolio composition shifts—we move away from high-return projects and prioritize projects that are more aligned with long-term environmental and social goals. This suggests that portfolios that prioritize sustainability are likely to achieve lower financial returns compared to those with fewer sustainability constraints. However, the figure also highlights that beyond a certain threshold, the reduction in returns becomes marginal, indicating that the impact of sustainability on returns is non-linear.

Experiment 4 at Figure 5 demonstrates the complex trade-offs inherent in strategic decision making when multiple constraints are in play. The portfolios near the top of the z-axis (higher sustainability) generally exhibit lower returns but those with a higher feasibility score maintain relatively stable returns. The figure highlights that portfolios with moderate levels of sustainability and high feasibility tend to be the most balanced options, offering reasonable returns while remaining practically implementable. On the other side, extreme portfolios (high in one dimension, low in others) often had higher but riskier returns.

Managerial Insights

The model assessment framework improves risk mitigation, enabling CEOs to evaluate not just financial risk-return but also strategic factors associated with potential partnerships or investments. These insights support a balanced approach to resource allocation, where high-return opportunities can be pursued with greater confidence, knowing that they align with the company's long-term resilience. The comparison between these unconstrained and the different constraint curves shows the impact of incorporating strategic variables on the portfolio optimization. A decision maker presented with Figure 2 has an explicit pictorial representation of the possibilities open to them, and the trade-offs involved. Points on the constrained Pareto curve represent solutions that not only optimize risk and return but also adhere to predefined thresholds of desirability, feasibility, and sustainability. By allowing a lower constraint, the ecosystem can yield more return or lower risk, resulting in a higher reward. However, maximizing the return-risk reward leads to a convergence in the top-right part of the curve, as there is typically only one project that achieves that specific reward. Reducing the risk-return reward results in various combinations of projects, leading to different curves and providing decision makers with flexibility in optimizing their portfolio based on their strategic priorities. For example, in Figure 2 of the port1 dataset, we see how for a minimum level of desirability (7.4) and the same return each time that we want solutions with a higher expected return we need to accept more risk. This can be quantified as the difference among the red line (maximum feasibility) and the green or yellow lines (lower feasibility). If the CEO were to prefer a portfolio easier to make it feasible, the return achieved will be lower.

6. Conclusions

We address a significant gap in the strategic management literature by employing computer-supported methods to enhance CEO decision making in the creation of corporate ecosystems. Drawing inspiration from He et al. [4] work on the portfolio optimization problem, our paper introduces a realistic and rich variant applied to strategic decision making. We have demonstrated that optimization algorithms can provide a valuable support in managing extensive datasets and complex decision-making scenarios efficiently. As a result, our findings can be summarized as follows: (i) computer-supported strategic decision making allows for quantifying trade-offs and reducing the time required for analysis; (ii) beyond financial metrics, our approach incorporates feasibility, desirability, and sustainability, which enables CEOs to optimize their utility functions considering multiple conflicting goals; (iii) the methodology provides valuable visualizations that aid in understanding the various trade-offs and benefits of potential strategies and ecosystem configurations.

Looking ahead, future research will focus on: (i) enhancing data collection by incorporating practical considerations and modeling stochastic returns with probability distributions; (ii) addressing biases in datasets and capturing subjective human meaning; (iii) integrating temporal dynamics of market maturity and its impacts on strategic decisions; (iv) analysing synergies among ecosystem players to capture interconnected relationships that drive strategic value beyond isolated metrics and (v) engaging with key stakeholders, partners, and customers to align the optimization processes with the real-world dynamics of corporate ecosystems.

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