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A Double Optimum New Solution Method Based on EVA and Knapsack

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Abstract: Optimizing resource allocation often requires a trade-off between multiple objectives. Since projects must be fully implemented or not at all, this issue is modeled as an integer programming problem, precisely a knapsack-type problem, where decision variables are binary (1 or 0). Projects may be complementary/supplementary and competitive/conflicting, meaning some are prerequisites for others, while some prevent others from being implemented. In this paper, a two-objective optimization model in the energy sector is developed, and the Non-dominated Sorting Genetic Algorithm III (NSGA III) is adopted to solve it because the NSGA-III method is capable of handling problems with non-linear characteristics as well as having multiple objectives. The objective is to maximize the overall portfolio's EVA (Economic Value Added). EVA is different from traditional performance measures and is more appropriate because it incorporates the objectives of all stakeholders in a business. Furthermore, because each project generates different kilowatts, maximizing the total production of the portfolio is appropriate. Data from the Greek energy market show optimal solutions on the Pareto efficiency front ranging from (14.7%, 38,000) to (11.91%, 40,750). This paper offers a transparent resource allocation process for similar issues in other sectors.

Keywords: portfolio management; mathematic programming; finance; decision-making; multi-objective optimization; mathematics of quantitative finance; mathematical models in optimal portfolio theory

1. Introduction

The rational allocation of resources is vital in both public and private sectors. A significant subset of the above is the problem of where to implement any project; the whole project must be completed rather than part of it. In this paper, we focus on the knapsack problem type according to Dantzig (1957). Particularly in Greece, due to the decade-long economic crisis and the coronavirus crisis, it is appropriate to allocate the limited budget as rationally and optimally as possible. The knapsack problem is a subclass of integer programming, achieving the optimal solution. Much scientific research has dealt with this issue, but it has yet to receive the appropriate attention in Greece.

We focus on the energy sector in Greece, which is developing rapidly and is attracting increasing interest in investment. In recent years, due to climate change, there has been an urgent need for conversion to alternative energy sources in line with the European policy objective of substantially increasing the share of renewable energy sources in electricity generation and more excellent absorption of funds from the European Recovery Fund.

In Greece, this interest is particularly evident in the case of the exploitation of wind energy due to the favorable legislative framework and the significant wind potential that exists in several Greek regions. Private investors are strongly motivated towards the exploitation of wind energy, mainly because the associated investment costs are not

prohibitive, and a somewhat favorable legislative framework ensures satisfactory rates of return (Mavrotas et al. 2003). Consequently, composing a portfolio with an optimal allocation of resources and an excellent strategic alignment based on future returns is crucial for companies to avoid fines and comply with legislation, as well as to develop scientific and technological capabilities that can help them drive innovation and gain competitive advantage (Bin et al. 2015).

The energy sector satisfies the knapsack problem's conditions and attracts attention to these problems. The challenges of traditional methods, including many runs, can be overcome using evolutionary strategies. In addition to guiding the search towards the Pareto optimal front, the goal of the multi-objective optimization technique is to maintain population diversity within a collection of non-dominated solutions. Among the most significant multi-objective optimization algorithms available today, the NSGA-III (Deb and Jain 2013; Jain and Deb 2013) is a potent strategy to overcome the shortcomings of NSGA-II, including its lack of uniform diversity and lateral diversity preserving operator. NSGA-III is selected among these algorithms because of its uniform diversity in obtaining the Pareto optimal front from a group of non-dominated solutions and its relatively greater capacity to handle many objectives.

Our approach takes into account the fact that some projects depend on others for implementation, such as an intermediate power station, while others cannot proceed without certain prerequisites being met. We categorize these dependencies into two matrices of complementary and conflicting investment projects and then use integer programming to identify the best investment option. Our approach differs from previous research as we utilize the EVA (Economic Value Added) index as an optimization goal. Typically, it is possible to select some investments with negative EVA if necessary to achieve maximum Eva for the portfolio as Sharma and Kumar (2010) found. When projects have different rates of return, cost and production must be considered during the maximization process. Each project's different production in megawatts results from different guaranteed price contracts (feed-in tariffs) or the exchange market, which varies over time.

Our model is further differentiated and idealized as an additional target of total portfolio energy production is added. This helps both to cover the investor in the event of a price decline and simultaneously meet each region's energy needs in the context of sustainable development. Our article first contributes to the debate on the use of EVA against revenue and the use of suitable data in a unique knapsack model for the energy sector of Greece that professionals and academics use. We attempt to use data from the Greek energy market that would be implemented in other countries' energy markets. The literature review and the main features of the energy sector selection are then presented, as well as the conclusions and discussion.

In the Section 2, we analyze the literature review relevant to the problem we consider. In the Section 3, we present the main research question. In the Section 4, we provide our data and the specific form of our model. In the Section 5, we provide the estimates and results. In the Section 6, we summarize all the above with our evaluation and attempt to find the rational answer to the main question.

2. Literature Review

Most research on knapsack problems has dealt with the version with a single constraint, e.g., Balas and Zemel (1980), Horowitz and Sahni (1974), Salkin and Kluyver (1975). Although the single-constraint version of this problem has received a lot of attention, the multi-constraint knapsack problem has not received proper attention in the Greek context (Jaszkiewicz 2004; Erlebach et al. 2002; Zitzler and Thiele 1999; Klamroth and Wiecek 2000). One of the first references to the multiple-constraint knapsack problem is by Lorie and Savage (1955) and Manne and Markowitz (1957) as a capital budgeting model. In Greece, a related study is provided by Florios et al. (2010).

The first accurate algorithms for the multi-constraint knapsack problem started in the 1960s. Gilmore and Gomory (1966) described a dynamic programming algorithm.

Later, Shih (1979) presented a branching and bounding algorithm for the multidimensional knapsack problem (MKP). In recent years, with the development of artificial intelligence, genetic algorithms can solve knapsack-type problems much faster with equally good results as the traditional methods (Kellerer et al. 2004; Khuri et al. 1994).

This paper divides the constraints into two categories: complementary and disjunctive. We use the negative disjunctive constraint as a particular case of a disjunctive constraint (Pferschy and Schauer 2017). Some papers dealing with the disjunctive constraint are Yamada et al. (2002), where a branch-and-bound algorithm is presented, and more recent exact computation algorithms are presented in Hifi and Otmani (2012) and Hifi et al. (2014). The 0-1 knapsack problem can be applied to various financial planning and portfolio management models. It determines which subset of assets provides the highest return under a given budget. The knapsack problem is a well-known combinatorial optimization problem with a wide range of business applications in capital budgeting (Bas 2011) and production planning (Camargo et al. 2012), among others.

Recent advancements in multi-objective optimization for the knapsack problem, particularly in energy portfolios, have introduced innovative methodologies. Notably, the Factored NSGA-II framework enhances exploration through overlapping subpopulations, effectively addressing multiple objectives such as profit maximization and weight minimization (Peerlinck and Sheppard 2022). Additionally, robust optimization algorithms have emerged, focusing on solutions resilient to variable changes, thereby broadening the solution space compared to traditional methods (Miyamoto and Fujiwara 2022).

The integration of quantum computing via the Quantum Approximate Optimization Algorithm (QAOA) presents a novel approach, demonstrating significant improvements in asset allocation within financial portfolios, which can be analogous to energy portfolio optimization (Huot et al. 2024), a great improvement on the previous topic provided by Awasthi et al. (2023). These methods collectively enhance the efficiency and effectiveness of solving complex multi-objective knapsack problems in energy contexts.

Faia et al. (2018) propose a portfolio optimization model using particle swarm optimization. This model addresses multi-objective challenges in energy markets by balancing risk and profit in energy portfolio decisions.

The hybrid algorithm combines k-nearest neighbor with quantum cuckoo search to enhance resource allocation solutions for the multidimensional knapsack problem, outperforming state-of-the-art algorithms in most instances (García and Maureira 2021).

The Harmony Search (HS) algorithm is a prominent heuristic for solving both single- and multi-objective 0-1 knapsack problems (KPs) and effectively solves single and multi-objective 0-1 knapsack problems (Adamuthe et al. 2020). Furthermore, innovations like the hybrid HS with distribution estimation have been proposed to avoid local optima, improving the algorithm's global search capabilities (Liu et al. 2022).

Dynamic Evolutionary Optimization (DEO) is increasingly applied to the multi-objective knapsack problem (MKP), addressing the complexities of real-world scenarios where objectives and constraints can change over time (de Queiroz Lafetá and Oliveira 2020).

Cacchiani et al. (2022) provide an excellent overview of solving techniques for the knapsack problem, especially the quadratic form. A novel optimization algorithm is designed to tackle the multidimensional knapsack problem (MKP), classified as NP-hard. This algorithm is an enhancement of the traditional moth search algorithm (MS), incorporating self-learning mechanisms to improve its efficiency and effectiveness (Feng and Wang 2022).

Lin et al. (2022) propose a single-preference-conditioned model to directly generate approximate Pareto solutions for any trade-off preference and design an efficient multi-objective reinforcement learning algorithm to train this model. Sur et al. (2022) adopted a deep reinforcement learning (DRL)-based approach; the experimental results indicate that the proposed method outperforms the random and greedy methods, particularly when the profits and weights of items have a non-linear relationship, such as quadratic forms. Nomer et al. (2020) introduce a heuristic solver based on neural networks and deep learning for the knapsack problem.

Olivas et al. (2021) conclude that incorporating fuzzy logic into hyperheuristics provides a robust mechanism for improving solutions to the knapsack problem. This approach enhances adaptability and results in better performance across various instances of the problem.

A new class of optimization problems called Mixed Pareto-Lexicographic Multi-objective Optimization Problems (MPL-MOPs) provides a suitable model for scenarios where some objectives have priority over others (Lai et al. 2020).

In the investment area, financial ratios such as the internal rate of return (IRR) and the Weighted Average Cost of Capital (WACC) play a vital role in the selection process of available investments (Kos et al. 2009). The financial measure IRR (internal rate of return) is widely applied in the financial and investment sector and, in many cases, is preferred to the NPV (Net Present Value), although NPV provides the highest accuracy. In this paper, we prefer IRR to reduce the computational cost to produce EVA, a critical investment indicator. EVA is a reliable way to evaluate whether some investments should be completed; it is possible to select some investments with a negative EVA if necessary to achieve maximum EVA for the portfolio (Sharma and Kumar 2010).

By integrating data science and advanced management strategies, organizations can optimize their portfolios to enhance profitability while minimizing environmental impacts. In recent years, scholars have been increasingly focused on EVA in relation to other methods of evaluating business performance. EVA has grown at a CAGR of 9.60%, compared to other business performance evaluation methods, which have only grown at a CAGR of 5.67%, as per publications in Scopus-listed journals (Tripathi et al. 2022).

In general, there are conflicting studies on EVA as a financial metric; (Faiteh and Mohammed 2023) state that EVA demonstrates superiority over traditional metrics for listed companies and can be adapted for unlisted firms using accounting beta, making it a versatile financial metric for value creation. According to Dobrowolski et al. (2022), on the other hand, EVA is not a universal financial metric; it fails to accurately reflect conditions in unstable markets, leading to potential mismanagement and limited shareholder value.

Chen et al. (2023b) found that EVA-related metrics naturally induce long-term, strategic and sustainable decision-making without limiting executives to overly focus on short-term profitability or develop a pseudo environment to illustrate EVA's managerial benefits and potential to cultivate sustainable growth.

A recent study relates to developing a mixed integer non-linear programming (MINLP) model that incorporates financial risk metrics into a robust closed-loop supply chain design, considering the unpredictability of final product demand to maximize EVA (Polo et al. 2019). Multi-objective optimization methods significantly impact optimization outcomes.

One well-known way to deal with this is the Weighted Sum Method. The objectives are often combined into a single objective, and conventional optimization procedures are employed to find the best solution. In this strategy, decision-makers must determine the weights. This method requires correct objective function weights and may not be suitable for nonconvex issues. Di Somma et al. (2018) suggested a stochastic integer programming model that converts the minimization of total energy costs and carbon dioxide emissions into a single objective using the weighted sum approach; then, they employed the branch-and-cut method to solve the researched issue.

In multi-objective evolutionary algorithms, a set of potential non-dominated solutions must be generated first, and the decision-maker selects from these solutions. There have been several reviews on the methods and application of multi-objective optimization (MOO). One of the most used methods is the Pareto method (Ehrgott 2005). The Pareto method is based on the principle of dominance where a dominated and a non-dominated solution emerges constantly from a continuously updated algorithm. The solution using the Pareto method generates a Pareto optimal front where it reflects the amount that must be sacrificed from the optimal solution of one objective to improve another objective.

In finance (Tapia and Coello 2007), to identify critical technical analysis patterns in financial time series, the niched-Pareto genetic algorithm (NPGA) is used. An alternative

method is the e-constraint method (Haimes et al. 1971) where all constraints are transformed into equality by adding or removing the appropriate constant (Mavrotas 2009; Mavrotas and Florios 2013). Mesquita-Cunha et al. (2023) developed a recent improvement of this algorithm for integer programming problems for knapsack-type resource allocation problems.

Genetic algorithms can also be applied to portfolio management (Metawa et al. 2016; Liu and Xiao 2021; Krink and Paterlini 2011). Giagkiozis and Fleming (2015) and Gunantara (2018) provide two comprehensive literature reviews of multi-objective optimization methods.

In the energy sector, optimizing portfolios is a critical concern, as it involves balancing various factors such as cost, risk, and renewable energy integration (Schönberger 2016). One approach to address this challenge is the use of the knapsack problem, a well-known optimization problem in the field of operations research (Ioannou et al. 2017)

The most common type of MOEA mentioned in the literature is dominance-based algorithms, specifically NSGA-II. Li and Qiu (2016) used an improved version of the NSGA-II to optimize a hydro-photovoltaic power system model, considering both power output smoothness and annual power generation. Noorollahi et al. (2017) created NSGA-II to solve a multi-objective problem. Indicator-based algorithms use indicator functions to assess population quality in MOEAs. Keshavarzzadeh and Ahmadi (2019) compared various strategies for optimizing a multi-objective model, including NSGA-II, generalized differential evaluation, indicator-based evolutionary algorithms, speed-constrained multi-objective algorithm, and strength Pareto algorithms.

The population quality in MOEAs is measured using indicator functions on indicator-based algorithms. Keshavarzzadeh and Ahmadi (2019) optimized a well-known multi-objective model using a variety of techniques, including NSGA-II, generalized differential evaluation, an indicator-based evolutionary algorithm, a speed-constrained multi-objective algorithm, and strong Pareto evolutionary algorithms. They then compared the outcomes of these algorithms.

Zhou et al. (2024) addresses the critical need for effective planning in integrated energy systems (IESs) to support energy revolution and sustainability goals. The authors propose a novel planning framework that integrates multi-objective optimization with fuzzy multi-criteria decision-making (MCDM). This framework is designed to tackle the complexities of IES planning by modeling it as a multi-objective optimization problem. The optimization problem is solved using a multi-objective state transition algorithm based on decomposition (MOSTA/D). This method generates a Pareto set that allows for trade-offs among conflicting objectives, which is a common challenge in multi-objective optimization.

The knapsack problem involves selecting a subset of items from a given set, where each item has a weight and a value, and the goal is to maximize the total value while staying within a weight constraint (Göteman et al. 2020).

Recent research has shown a significant increase in the application of optimization techniques, including the knapsack problem, to address energy-related challenges. For example, goal programming has been used to balance the trade-off between the cost per kWh of an electricity generation portfolio and the total risk for an investor-owned utility (Ioannou et al. 2017).

Chen et al. (2023a) reviewed multi-objective optimization in long-term energy systems, emphasizing the need to consider economic, environmental, and energy security objectives to address complex energy demands.

Recent advanced studies have used machine learning or reinforcement learning in portfolio management. Vaish et al. (2024) introduce the use of the Random Forest (RF) model, a popular machine learning algorithm, for optimizing microgrid configurations. The paper compares the RF model's performance with other methodologies, such as particle swarm optimization (PSO) and artificial neural networks (ANNs), indicating a growing trend in applying machine learning techniques to energy optimization problems.

A comprehensive overview of new machine learning techniques in the field of the energy sector is provided by Alazemi et al. (2024).

An alternative approach is the RNN for asset allocation management (Giacomazzi Dantas 2021; Milhomem and Dantas 2021; Tao et al. 2021). deLlano-Paz et al. (2017) provide a comprehensive literature survey on applying Modern Portfolio Theory (MPT) in energy planning.

The model proposed by Roques et al. (2010) seeks to identify the portfolio consisting of those European plants (inter-State12) that minimize the variability of the wind production output for a specific production level as an objective function. They propose an alternative definition for return, referring to it as the mean capacity factor for the different locations. Risk is defined as the hourly variability of production (Rombauts et al. 2011).

Overall, the literature review highlights the growing importance of the knapsack problem in optimizing energy portfolios, as it provides a valuable tool for balancing various objectives and constraints in the energy sector.

3. The Main Question from a Theoretical Point of View—Methodology

Our main question is, "Is there a rational and efficient way to allocate a given amount of budget to a set of projects among alternatives to achieve maximum profitability?". Our variables are Boolean for selected and unselected projects. In this way, the problem is treated as a budget problem (knapsack). A project is selected to be covered by the budget if the total profitability of the selected projects is maximum. We develop our model to solve this problem by answering the main question.

We consider the classical 0-1 knapsack problem, where a subset of n data projects must be allocated to a knapsack of capacity c. Each project has a profit r_j and a weight w_j, and the goal is to select a fraction of projects that maximize the total profit without exceeding the available budget. A binary variable $X_j = 0$ or 1 is defined because each project must be implemented as a whole or not at all. Several variations of the knapsack problem have been proposed to help organizations make sound project selection decisions in different sectors (Martello and Toth 1990).

We use an integer programming formulation (0-1) where there is a binary decision variable for each alternative, and these take values of 0 (alternative not selected) or 1 (alternative selected). In the case of a target, an integer programming (IP) formulation is usually preferred, particularly the knapsack formulation. We construct the model using linear algebra to achieve a practical way to implement several subproblems with different efficiency rates. Another subproblem arises among projects: One project is independent of another; one project is complementary to another; one project is disjoint-conflicting. Thus, the model is defined for the three categories of constraints as follows:

Matrix of Decision Variables X

$$X_{1\times n} = [x_i] = [x_1, x_2, x_3, \ldots . x_n] \ \forall i = 1, 2 \ldots n \ projects \tag{1}$$

where x_i is the binary variable 1 or 0 if the project i is implemented or not.

Matrix cost of projects C

$$C_{1\times n} = [c_i] = [c_1, c_2, c_3, \ldots . c_n] \ \forall i = 1, 2 \ldots n \ projects \tag{2}$$

where c_i is the specific cost for each project construction.

Matrix of Production of Projects

$$P_{1\times n} = [p_i] = \left[p_1, p_2, p_3, \ldots . p_n\right] \ \forall i = 1, 2 \ldots n \ projects \tag{3}$$

where p_i is the specific production for each project at Megawatts (MW).

Matrix of Return of Projects

$$R_{1\times n} = [r_i] = [r_1, r_2, r_3, \ldots . r_n] \ \forall i = 1, 2 \ldots n \ projects \tag{4}$$

where r_i is the specific return for each project as a percentage of the cost.

Matrix ROICC= *Return − OPPEX*

$$R'_{1 \times n} = \left[r'_i \right] = \left[r'_1, r'_2, r'_3, \ldots r'_n \right] \; \forall i = 1, 2 \ldots n \; projects \tag{5}$$

$$WACC = i_s \frac{E}{E + DTE * E} + (1 - \varphi) i_D \frac{DTE * E}{E + DTE * E} \tag{6}$$

Objective Function (O.F)

$$\textbf{Max O.F 1} \; \mathbf{X_{1 \times n}} \times (ROICC - WACC) \; \forall i = 1, 2 \ldots n \; projects \tag{7}$$

$$\textbf{Max O.F 2} \; \mathbf{X_{1 \times n}} \times \mathbf{P_{1 \times n}}^T \; \forall i = 1, 2 \ldots n \; projects \tag{8}$$

Constraints:

Budget restriction

$$\textbf{KNAPSACK} \; \mathbf{X_{1 \times n}} \times \mathbf{C^T_{1 \times n}} = \textbf{KNAPSACK}_{1 \times 1} \; \forall i = 1, 2 \ldots n \; projects \tag{9}$$

Nowadays, particularly in Greece because of the prolonged recession after the economic crisis of 2008 and the current coronavirus pandemic, it is imperative to use the available budget in the best possible way. To achieve this, the key role is in the conversion of traditional investments to alternative and modern investments such as renewable sources of energy. In this area, another critical issue emerges, which is the complementarity and competitiveness of projects.

Complementarity is very important because it indicates that implementation of a project is impossible and unprofitable without another project being completed first. This second point reveals a precise need for further research on the subject. It is possible that a project is not only necessary for the realization of an investment but may also meet the needs of other investments that can be carried out with the remaining available budget. A feature example is an energy station that meets the energy needs of multiple energy investments, such as photovoltaics or windmills.

On the other hand, competitiveness means that if an investment is made, one or more available investments cannot be created. It is very important that the available budget is not wasted and that the selection of investments is carried out objectively so that the plurality of all types of investments in the portfolio is appropriate. In the energy sector, this is achieved by not allowing several investments of one type to be made at the same time and by not making more investments in an area where the availability of energy needs is met.

Conflict projects A

$A_{n \times k} = \left[a_{ij} \right]$ where i = projects and j = group of conflict projects

So $i = n$ and $j = k$, $a_{ij} = [1, 0]$ where 1 means projects are conflicting and zero in any other cases.

$$X_{1 \times n} \times A_{n \times k} \leq 1_{1 \times k} \; \forall i = 1, 2 \ldots n \; projects \tag{10}$$

Complementary projects S

$\mathbf{S_{n \times m}} = \left[\mathbf{b_{ij}} \right]$ where **i** = projects and **j** = group of projects in combination.

So $\mathbf{i = n}$ and $\mathbf{j = m}$, $\mathbf{b_{ij}} = [\mathbf{1, -1, 0}]$ where 1 and −1, respectively, mean projects are in combination, and 0 in any other cases.

$$X_{1 \times n} \times S_{n \times m} \leq 0_{1 \times m} \; \forall i = 1, 2 \ldots n \; projects \tag{11}$$

To reduce the dimension of the table: If there are z projects in combination with another project, respectively, the table of complementary projects is transformed.

$i = n$ and $j = m$, $b_{ij} = [\mathbf{1}, -z, \mathbf{0}]$ where 1 is if the project is combined with another and -z indicates an energy station project to be created if any of the above is carried out, and 0 for all other cases.

$$X_{1 \times n} \times S_{n \times m} \leq 0_{1 \times m} \ \forall i = 1, 2 \ldots n \ projects \tag{12}$$

With the last two equations from the financial position, we ensure that the concentration risk in our portfolio is kept low, and from the ethical point of view, we avoid a biased position in a particular type of investment.

$$WACC = i_s \times \frac{S}{D + S} + i_D \times (1 - \varphi) \times \frac{D}{D + S} \tag{13}$$

According to the INTERNATIONAL VALUATION STANDARDS COUNCIL (IVSC) each investor requires a different rate of return (i_s) depending on the type of investment (photovoltaics or windmill). Similarly, banks vary the mortgage rate (i_D) according to the type of investment and, in addition, the creditworthiness of the investor. For this reason, in our model, each project has a different rate of return. Another important measure is the ratio of investors' capital S/(D + S) and banks' D/(D + S) achieved through the leverage, processing the essential capital to maximize profit, and φ represents tax rate.

The Weighted Average Cost of Capital (WACC) represents the average rate of return a company must pay to finance its assets, calculated as a weighted sum of the costs of equity and debt. It reflects the minimum return required by investors and is crucial for evaluating investment decisions, as it serves as the discount rate in capital budgeting and valuation models. WACC incorporates the firm's capital structure and market risk to provide a comprehensive financing cost.

Another question that arises about the profitability of this project is as follows: We first assume that profitability is equal to the NPV of each project. If the profitability of the rate of return is IRR, then we lose the upper part of our profit using the discount factor of the NPV of each project if we replace the rate of return with the Average Return on Invested Capital (AROIC) of each project. The ROIC substitution must be calculated using present values to turn our problem into a linear algebra problem where a matrix R or X or C must be diagonal, and we choose C because the investment amount of each project cost is not involved with complementarity and discrimination-conflict constraints. Based on Liapis (2010), we would also like to produce an EVA vector of each project (Stewart 2009). The reason for all this transformation is to introduce the EVA theory into the problem.

Economic Value Added (EVA) is a performance measurement tool used to assess a company's ability to generate value beyond the required return on its invested capital. It is calculated by subtracting the cost of capital from the firm's net operating profit after taxes (NOPAT). EVA emphasizes the importance of creating shareholder wealth by ensuring returns exceed the opportunity cost of capital employed.

Subtracting (12) by (5), the O.F gives the following:

$$\begin{aligned} &X_{1 \times n} \times C_{n \times n}^D \times R'^T_{n \times 1} \ - \\ &X_{1 \times n} \times C_{n \times n}^D \times WACC_{n \times 1} \Leftrightarrow \\ &X_{1 \times n} \times C_{n \times n}^D \times \left[R'^T - WACC \right]_{n \times 1} \Leftrightarrow \\ &X_{1 \times n} \times C_{n \times n}^D \times EVA_{n \times 1} = Profit_{1 \times 1} \ \forall i = 1, 2 \ldots n \ projects \end{aligned} \tag{14}$$

With the abovementioned approach, an EVA vector is critical for knapsack fulfillment. All the above transformations give the value of a different approach to decision-making for the multiple-investment problem under knapsack constraints.

Many projects may have negative EVA in addition to our constraints so a new filter should be imposed as follows: Eva ≥ 0 or Ri $\geq$ WACC

$C \times X_i$ could be a stepwise product, but for EVA to be accurate for each project, WACC should be a vector with the same number of elements.

Another issue concerning WACC is the combination of different types of capital reflected through leverage, which can vary from project to project. Using the preferred capital, competitiveness and complementarity between projects, in addition to technical and economic reasons, depends on environmental and socio-regulatory factors.

We selected the NSGA III algorithm to address the given problem as the Pareto front (trade-off) between objectives is nonconvex and because the problem has complex non-linear characteristics.

1. NSGA-III is designed to handle more difficult computations and constraints, especially in cases with many decision variables. The algorithm manages to simultaneously optimize multiple dimensions without degrading the quality of solutions and offers better allocation in problems with complex solution sets.
2. In problems with many iterations (looping structures) and complex constraints, NSGA-III can handle complexity better because it searches in multidimensional space and uses reference points to find solutions in each part of the objective space. The constraints are considered through the non-dominated classification process and the distance strategy from the reference points.
3. NSGA-III is known for its ability to explore the multidimensional solution space more fully through the Niche Preservation process and the way it manages benchmarks. This allows it to find solutions that may not be easily identified by NSGA-II. In NSGA-II, solutions close to the Pareto front can be clustered in specific regions, leaving other regions empty. NSGA-III, however, uses a strategy that ensures that solutions are evenly distributed along the Pareto front.
4. A better advantage of NSGA-III is that it does not require additional parameters compared to NSGA-II.

The Non-dominated Sorting Genetic Algorithm III (NSGA-III) is a powerful multi-objective optimization technique designed to handle problems involving many objectives. It extends the concepts of NSGA-II by introducing a reference-point-based approach to maintain a well-distributed set of Pareto optimal solutions. Unlike NSGA-II, which uses crowding distance to promote diversity, NSGA-III uses predefined reference points to guide the search process toward a more uniform spread across the objective space. This makes it particularly useful in high-dimensional objective spaces, where maintaining diversity becomes challenging.

NSGA-III begins by generating an initial population, evaluating it based on the objectives, and sorting individuals into different Pareto fronts. It then associates each solution with the nearest reference point, preserving niche diversity by selecting one solution per reference point. The population evolves through evolutionary operators such as selection, crossover, and mutation, iteratively refining the Pareto front. The algorithm continues until a stopping criterion is met, such as a maximum number of generations or a convergence criterion where the solutions do not significantly improve. NSGA-III's ability to produce diverse solutions makes it suitable for complex, real-world applications with multiple conflicting objectives.

Step-by-step representation of NSGA III pseudo code is shown in Appendix A.

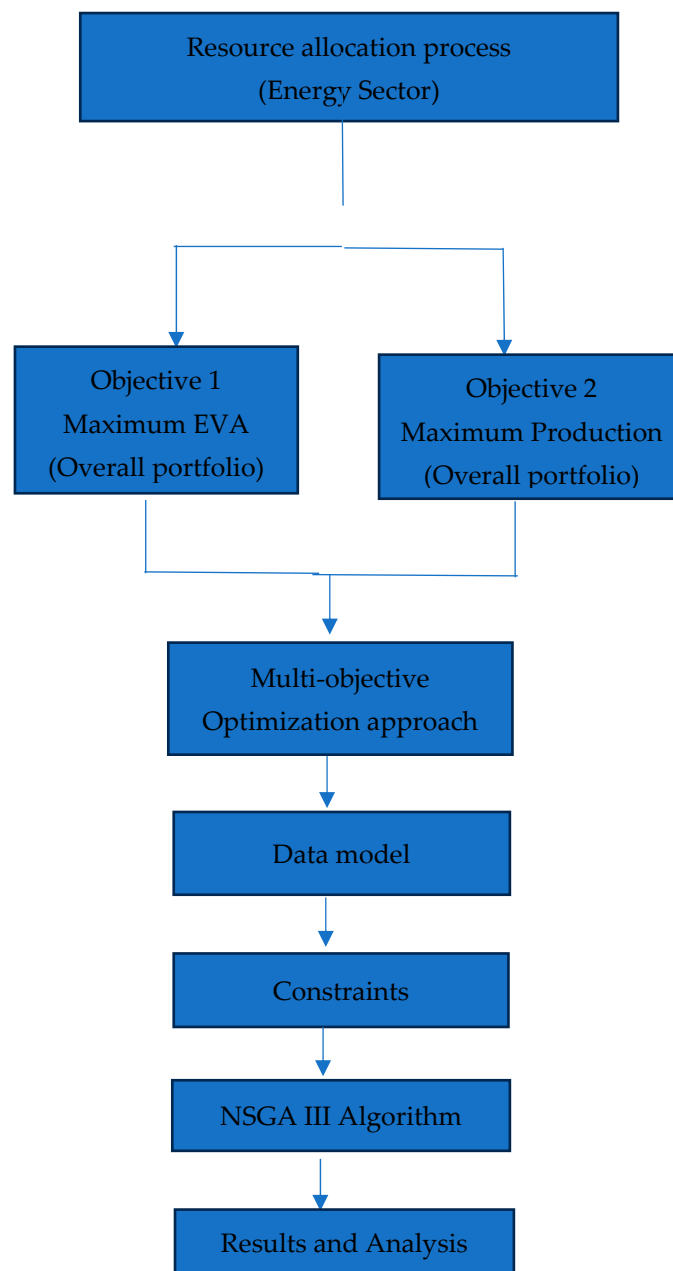An overview of this paper is shown in Figure 1.

Figure 1. Flow chart of process (Source: Author's calculations).

4. Data and Model

We use data from the Greek green energy market; we have fifteen alternative investment types of projects: four windmills, thirteen photovoltaics, and three power stations. A budget volume analysis is conducted of the windmills, photovoltaics and mandatory connection infrastructure. These types of projects have a mean rate of return, and the infrastructure has returns derived from other projects. Our specific model and data tables are provided below. The budget volume is allocated between equity or equity capital and debt capital using a leverage ratio, a financial metric that measures the proportion of a company's capital that comes from debt. The energy station is expressed at 0.2€ and a return of 6%, which is identical to the WACC because the energy station does not individually generate ROIC but is suitable to generate another project.

Objective Function:

$$O.F_1 = \sum_{i=1}^{20} [X_i \times (ROICC_i - WACC_i)] \qquad \forall\, i = 1, 2 \ldots n\ projects \tag{15}$$

$$O.F_2 = \sum_{i=1}^{20} [X_i \times (P_i^{\ T})] \qquad \forall\, i = 1, 2 \ldots n\ projects \tag{16}$$

$$EVA^T = [EVA_i] = [EVA_1, EVA_2, \ldots EVA_{20}] \qquad \forall\, i = 1, 2 \ldots n\ projects \tag{17}$$

$$EVA_i = r'_i - wacc_i \qquad \forall\, i = 1, 2 \ldots n\ projects \tag{18}$$

$$r'_i = \text{ROIC of each project} \qquad \forall\, i = 1, 2 \ldots n\ projects$$

Budget = 15 million €

WACC: A table of WACC for each project

$$i_s = 15\%,\ i_d = 6\%,\ \varphi = 22\%$$

P8, P13, and P15 represent the energy plants where they do not provide a profit on their own but are necessary for the operation of the other types of investments, and therefore, EVA = 0.

Restrictions:

P1 or P3 or P14 (19)

P12 and P5 and P16 then P8 (20)

P11 and P4 then P15 (21)

P7 or P9 (22)

$$X12 \times P12 + X5 \times P5 + X16 \times P16\ \geq 14000 \tag{23}$$

$$X11 \times P11 + X4 \times P4\ \geq 3000 \tag{24}$$

$$\sum_{i=1}^{20} X_i \times C_i \leq Budget \quad \forall\, i = 1, 2 \ldots n\ projects \tag{25}$$

Explanations of the restrictions:

Only one of the investments P1, P2, and P14 can be implemented according to

$$x_1 + x_3 + x_{14} \leq 1. \tag{26}$$

P8 represents a power station, and P4, P5, and P17 are photovoltaic investments that will be built in the same area. If at least one of the three is implemented, it is appropriate to create P8 because it will meet the energy needs of all 3. The equation that represents this is

$$x_{12} + x_5 + x_{16} - 3x_8 \leq 0. \tag{27}$$

P15 represents a power station, and P11 and P6 are photovoltaic investments that will be created in the same area. If at least one of the two is implemented, P15 is appropriate to be created because it will meet the energy needs of both. The equation representing this is

$$x_{11} + x_4 - 2x_{15} \leq 0. \tag{28}$$

Only one of P4 and P6 can be implemented according to the following equation:

$$x_7 + x_9 \leq 1. \tag{29}$$

Projects under constraint 2 must, if an energy station is built, cover the minimum energy needs of the region.

Projects falling under restriction 3 must, if an energy station is built, cover at least the minimum energy needs of the area.

The total cost must not exceed the available budget:

$$Budget \leq 15000000\ € \tag{30}$$

In Table 1, the cost and ROIC of available investment projects and power plants provide information on the investment projects.

Table 1. Data on investment projects.

	Cost	Production	Price	Revenue	Type	DTE
P1	5.00 €	18,000	50 €	0.9 €	Windmill	4
P2	3.00 €	9750	40 €	0.39 €	Windmill	2
P3	4.00 €	10,000	60 €	0.6 €	Windmill	3
P4	1.00 €	2300	65 €	0.15 €	Photovoltaics	4
P5	0.75 €	1200	68 €	0.081 €	Photovoltaics	2
P6	1.50 €	2800	70 €	0.196 €	Photovoltaics	3
P7	0.60 €	1250	72 €	0.09 €	Photovoltaics	4
P8	0.20 €				Electric Station	
P9	0.40 €	850	75 €	0.063 €	Photovoltaics	4
P10	0.50 €	750	66 €	0.049 €	Photovoltaics	2
P11	1.00 €	1500	74 €	0.111 €	Photovoltaics	2
P12	0.50 €	700	65 €	0.045 €	Photovoltaics	2
P13	0.20 €				Electric Station	
P14	4.00 €	14,000	45 €	0.63 €	Windmill	4
P15	0.20 €				Electric Station	
P16	5.00 €	13,500	63 €	0.85 €	Photovoltaics	4
P17	0.70 €	830	67 €	0.055 €	Photovoltaics	2
P18	0.80 €	770	70 €	0.053 €	Photovoltaics	2
P19	2.00 €	4750	63 €	0.299 €	Photovoltaics	4
P20	1.45 €	2230	65 €	0.15 €	Photovoltaics	2

Source: Data from the Greek energy market.

5. Estimations and Results

Using the NSGA III algorithm and matrix calculations, our findings are provided below:

In Table 2, the appropriate formulation gives the table for constraint Equations (26)–(29) according to a general form of Equations (10)–(12) (e.g., if project 1 and project 2 are conflicting, then the equation representing them is $x_7 + x_9 \leq 1$. If projects 3 and 4 are complementary to project 5 of the energy station, then the corresponding equation is $x_{11} + x_4 - 2 \times x_{15} \leq 0$).

Table 2. Matrixes of complementary and conflict projects.

	Conflict		Complementary	
X1	1	0	0	0
X2	0	0	0	0
X3	1	0	0	0
X4	0	0	0	1
X5	0	0	1	0
X6	0	0	0	0
X7	0	1	0	0
X8	0	0	−3	0
X9	0	1	0	0
X10	0	0	0	0

Table 2. *Cont.*

	Conflict			**Complementary**	
X11	0	0		0	1
X12	0	0		1	0
X13	0	0		0	0
X14	1	0		0	0
X15	0	0		0	−2
X16	0	0		1	0
X17	0	0		0	0
X18	0	0		0	0
X19	0	0		0	0
X20	0	0		0	0
	RESTRICTIONS			RESTRICTIONS	
X × A	1	0	X × S	−1	0
	≤			≤	
	LIMIT OF RESTRICTIONS			LIMIT OF RESTRICTIONS	
	1	1		0	0

Source: Author's calculations.

In Table 3, the appropriate formulation gives the table for constraint Equations (23) and (24).

Table 3. Matrixes of complementary and conflict projects.

	Production	**Conflict**	
X1	18,000	0	0
X2	9750	0	0
X3	10,000	0	0
X4	2300		0
X5	1200	0	0
X6	2800	0	0
X7	1250	0	1
X8			0
X9	850	0	1
X10	750	0	0
X11	1500		0
X12	700	700	0
X13		0	0
X14	14,000	0	0
X15		0	0
X16	13,500	13,500	0
X17	830	0	0
X18	770	0	0

Table 3. *Cont.*

	Production	Conflict	
	Production	**Conflict**	
X19	4750	0	0
X20	2230	0	0
		RESTRICTIONS	
$X \times P^T$	14,200	38,000	
	$\geq$		
	LIMIT OF RESTRICTIONS		
	14,000	30,000	

Table 4 presents the details of each eligible or ineligible project.

Table 4. Structure of an optimal portfolio.

	EVA = ROIC − WACC	**ROIC**	**WACC**	**COST** [D]	**X**	**SELECTED PROJECTS**
X1	6%	13%	6.7%	5.00 €	0	WINDMILL
X2	0%	8%	8.1%	3.00 €	1	-
X3	3%	10%	7.3%	4.00 €	0	-
X4	3%	10%	6.7%	1.00 €	1	-
X5	−2%	6%	8.1%	0.75 €	0	PHOTOVOLTAICS
X6	1%	8%	7.3%	1.50 €	0	PHOTOVOLTAICS
X7	3%	10%	6.7%	0.60 €	0	-
X8	0%	0%	0%	0.20 €	1	ENERGY STATION
X9	4%	11%	6.7%	0.40 €	0	-
X10	−3%	5%	8.1%	0.50 €	0	-
X11	−2%	6%	8.1%	1.00 €	1	PHOTOVOLTAICS
X12	−4%	4%	8.1%	0.50 €	1	PHOTOVOLTAICS
X13	0%	0%	0%	0.20 €	0	-
X14	4%	11%	6.7%	4.00 €	1	WINDMILL
X15	0%	0%	0%	0.20 €	1	ENERGY STATION
X16	5%	12%	6.7%	5.00 €	1	PHOTOVOLTAICS
X17	−5%	3%	8.1%	0.70 €	0	-
X18	−4%	4%	8.1%	0.80 €	0	-
X19	0%	3%	6.7%	2.00 €	0	-
X20	1%	−3%	8.1%	1.45 €	0	-

Source: Author's calculations. D referred to diagonal matrix.

The EVA of power stations is 0% because they do not generate a profit, but they are suitable for the creation of another project.

Table 5 presents an estimation of the Objective Functions (OFs)—total EVA or PROFIT, total production, and total budget,

Table 5. Optimal portfolio OF.

MAX EVA OF KNAPSACK	**11.91%**
FULFIL OF KNAPSACK = X × C	**14.9 €**
MAX PRODUCTION	**40,750**

Source: Author's calculations.

Figure 2 reflects the Pareto efficient front, and the optimal solutions (Max EVA, Max Production) range from 14.7% (38,000) to 11.91% (40,750).
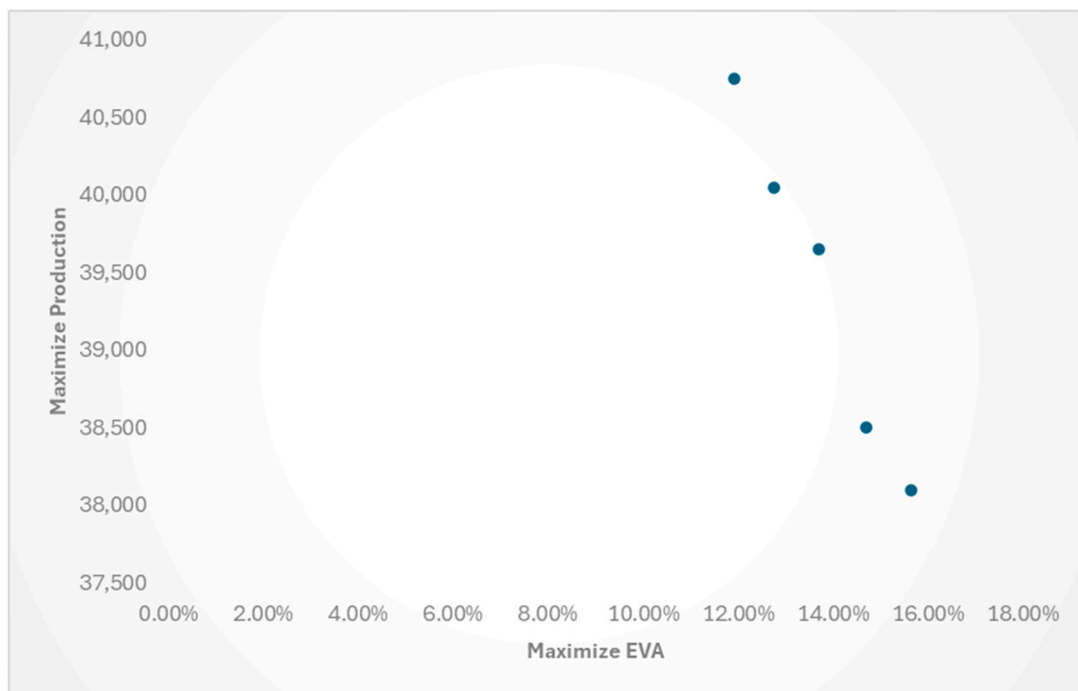
Figure 2. Pareto front (Source: Author's calculations).

Data from any project similar to the data we used from the Greek Green Energy Market, which are taken from a case study, can be used.

From the above estimation, it is concluded that the optimal portfolio structure is as follows:

1. Fulfilling the knapsack—budget: In our example, the optimal budget to be consumed is 14.9 M€.
2. Selection of projects xi: Our optimal portfolio structure includes projects P1, P4, P11, P12 and P19, P16 and power plants P8 and P15.
3. OF 1: The optimal profit is 11.91%.
4. OF 2: Optimal production 40,750.

6. Discussions and Conclusions

6.1. Discussions and Key Findings

The paper aims to extend the existing literature on portfolio optimization in the energy market. From the overall analysis carried out in this case study, its contribution to the optimal allocation of budget resources lies in constructing a specialized model for energy projects based on the data of the Greek energy market.

The paper presents a novel optimization approach to resource allocation in the energy sector, employing a combination of Economic Value Added (EVA) and the knapsack problem. The authors developed a double optimization model within a knapsack-type

framework using the NSGA III algorithm. The research focuses on maximizing EVA alongside production levels to enhance decision-making in the energy sector, particularly in Greece. Applying the model to the Greek energy market offers valuable insights, especially in balancing investments in renewable energy, such as wind power, against overall portfolio returns.

This study has several findings.

First, complementarity and competitiveness between projects are key issues addressed in this paper. Its contribution to this issue is that the creation of alternative constraints to the primary Boolean type of problem of the variable to perform or not to perform a project is always an integer, which does not allow continuous mathematical approximations (Pferschy and Schauer 2017).

Second, in this paper, financial science enters the problem, and mainly the objective function, by maximizing the Economic Value Added (EVA) in the optimal projects for the part of the Economic Value Added that constitutes the knapsack budget (Dluhopolskyi et al. 2021). In this way, the optimal projects that constitute the portfolio knapsack are decided by the firm's management, not by the shareholders or banks.

Third, maximizing EVA while maximizing production using the NSGA III algorithm (Eftekharian et al. 2017) that we carried out in our paper is an innovation that focuses on decision-making according to the objectives of the company's management while meeting the energy needs of the region through maximizing production, ensuring that in a period of price decrease, there will not be a significant impact on the EVA of the portfolio (Vazhayil and Balasubramanian 2014).

Fourth, introducing the constant WACC vector per project allows the introduction of leverage per project and the differentiation of the cost of each project while differentiating the cost of capital per project type in energy from the IVSC studies. Finally, for a given budget, it seems that if you want to increase production, the increase in production must "sacrifice" some of the EVA. This is because elective projects are likely to have higher costs.

The strength of the paper lies in its straightforward methodological approach and the innovative use of EVA as a financial metric alongside a traditional knapsack problem to address the complexities of energy portfolio management. The authors differentiate their approach from previous work by introducing a constant WACC vector per project and incorporating the concept of sacrificing some EVA for production maximization, offering a fresh perspective in multi-objective optimization.

6.2. Theoretical Implication and Practical Implication

This study enriches the theoretical research of optimal allocation and portfolio optimization approach in the energy market. The originality lies in the contribution of a specific methodology to decision-making for selecting specific projects in the energy sector instead of the simple and project-specific financial methods, NPV–IRR. The theoretical implication of the article contributes to the academic debate on whether the EVA index can offer better results than traditional indicators, especially in the energy sector (Dobrowolski et al. 2022).

Also, following the multi-objective optimization approach, it tries to find the balance between the optimization of the financial objective (EVA), ensuring that in a period of price decrease, there will not be a significant impact on the EVA of the portfolio. The second objective is to maximize the production of the portfolio covering, in addition to the above objective, the objective of sustainable development meeting the energy needs of each region. The practical application depends on the fact that the model we develop is not a theoretical model but a model of operational research for market practitioners. Each investor can adjust the model to his needs depending on the specific characteristics of the projects they have to choose from and the regions where they are located. Data from the Greek energy market were used to further enrich scientific approaches in the professional field, helping qualified executives make more rational decisions.

6.3. Restrictions and Future Work

Although this study provides valuable insights, there are some restrictions. First, the data on the Greek energy market we used are limited. A second observation is that the decline in portfolio EVA is disproportionate to the increase in the output provided by this "sacrifice". This is probably due to the specific projects to be selected. Third, the optimal solution to the problem is reached relatively quickly, which explains why the Pareto front of this form is, as in Figure 1, influenced by the above two factors.

The next stage of the research will be to expand the available projects for selection and to see if this problem has been eliminated. However, as these projects belong to the photovoltaic sector, the result is expected to stay the same. A large part of the cost comes from creating energy plants, a sufficient and necessary condition that increases costs without producing a direct economic benefit. The restriction to cover the energy needs of each region has also been introduced, which 'sacrifices' part of the purely financial objective for the benefit of society.

An extension of our research would be the introduction of the theory of representation and the constraints it defines between the management–shareholder–banking relations. According to agent theory and Stewart's EVA, it seeks to build a portfolio that satisfies all three parties (banks, shareholders, and managers) because investors handle money from funds and form portfolios from managers, so it is more appropriate to choose the EVA which managers use to secure their fees, and when EVA is positive, both managers and creditors are satisfied. The specific data refer to Greece; any international investor can use the model by importing data from another economy.

Future research should consider networks' availability regarding loads at different times and other technical specifications. Network inefficiencies, which result from losses for both the type of project and the area of implementation, affect both production and price.

Author Contributions: K.L., in collaboration with T.P., conceived the idea and wrote the conclusions. P.P. wrote the introduction, the literature review, and the empirical results. E.C. performed the empirical evidence and wrote the final text. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data we use for our calculations are derived from the Greek Energy Market.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Algorithm A1: Generation t of NSGA-III Procedure
Input: H structured reference points Z* or supplied aspiration points Z*, parent population Pt Output: P_{t+1} 1. $S_t = \varnothing$ 2. Q_t = Recombination + Mutation (P_t) 3. $R_t = P_t \cup Q_t$ 4. (F_1, F_2, ...) = Non-dominated-sort (R_t) 5. repeat 6. $S_t = S_t \cup F_i$ and i = i + 1 7. until $\lvert S_t \rvert \geq N$ 8. Last front to be included: $F_l = F_i$ 9. if $\lvert S_t \rvert = N$ then 10. $P_{t+1} = S_t$, break 11. else

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Algorithm A1: *Cont.*

---

12. $P_{t+1} = \bigcup_{j=1}^{l-1} F_j$

13. Point to chosen from F_l: K = N − |P_{t+1}|

14. Normalize objectives and create reference set Z*:

Normalize (f^n, S_t, Z^r, Z^s, Z^a)

15. Associate each member s of S_t with a reference point:

[π(s),d(s)] = Associate (S_t, Z*)

16. Compute niche count of reference point

j ∈ Z*: $\rho_j = \sum_{s \in s_t / F_i} ((\pi(s) = j)?1:0)$

17. Choose K members one at a time from Fl to construct P_{t+1}:

Niching(K, ρ_j, π, d, Z^r, F_l, P_{t+1})

18. end if

Step-1 Normalize f^n, S_t, Z^r, Z^s/Z^a) procedure

Input: St, Z^s (structured points) or Z^a (supplied points)

Output: f^n, Z^r (reference points on normalized hyper-plane)

1. for j = 1 to M do

2.   Compute ideal point: z_j^{min} = min$_{s \in St}$ f_j(s)

3.   Translate objectives: fj'(s) = fj(s) − z_j^{min} ∀s ∈ St

4.   Compute extreme points: z^{jmax} = s:

argmins $_{\in St}$ ASF(s, w^j) = (ϵ, ..., ϵ)^T),

ϵ = 10^{-6} and w_i^j = 1

5. end for

6. Compute intercepts a_j for j= 1, M

7. Normalize objectives (f^n) using

$f_i^n(X) = \frac{f'_i(X)}{a_i - Z_i^{min}}$, for i = 1, 2, ..., M

8. if Z^a is given then

9.   Map each (aspiration) point on normalized hyper-plane

and save the points in the set Z'

10. else

11. Z^r = Z^s

12. end if

Step-2 Associate (S_t, Z^r) procedure

Input: S_t, Z^r

Output: π (s ∈ S_t), d(s ∈ S_t)

1. for each reference point Z ∈ Z^r do

2.   Compute $_{reference}$ line w = z

3. end for

4. for each (s ∈ S_t) do

5.   for each w ∈ Z^r do

6.   Compute $d^\perp$(s, w) = s − w^Ts / ||w||

7.   end for

8.   Assign π(s) = w: argmin $_{w \in Z^r}$ $d^\perp$(s, w)

9.   Assign d(s) = $d^\perp$(s, π(s))

10. end for

Step-3 Niching (K, ρ_j, π, d, Z^r, F_l, P_{t+1}) procedure

Input: K, ρ_j, π(s ∈ S_t), d(s ∈ S_t), Z^r, F_l

Output: P_{t+1}

1. k = 1

2. while k ≤ K do

3. J_{min} = {j: argmin $_{j \in Zr}$ ρj}

4. $\bar{J}$ = random (j_{min})

5.   Ij = {s: π(s) = j, s ∈ Fl}

Algorithm A1: *Cont.*
6.   if $I_{\bar{J}} \neq \varnothing$ then
7.   if $\rho_j = 0$ then
8. $P_{t+1} = P_{t+1} \cup \{s: \text{argmin}_{s \in I_{\bar{J}}} ds\}$
9.   else
10. $P_{t+1} = P_{t+1} \cup \text{random}\left(I_{\bar{J}}\right)$
11.   end if
12. $\rho_j = \rho_j + 1$, $F_l = F_l / s$
13. $k = k + 1$
14. else
15. $Z^r = Z^r / \{\bar{J}\}$
16. end if
17. end while

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