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Mathematical model for budget distribution and allocation using a multi-objective particle swarm optimization algorithm

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Abstract

This study aims to present a budgeting model for organizational development projects that enables the efficient allocation and distribution of budgets across various sectors. A tri-objective budgeting model was developed and examined for implementation in Shirvan City. The proposed approach utilizes the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm to optimize the model under investigation. The results of the proposed method indicate that employing the MOPSO algorithm leads to efficient budget allocation and distribution. In many organizations, resource allocation is still reliant on traditional and outdated methods, which often encounter significant challenges and inherent errors. Therefore, adopting a method that leverages mathematical models to determine optimal and effective allocation is of critical importance. Budgeting is recognized as an effective and efficient tool for achieving organizational objectives and resource allocation. This allocation process provides a system for controlling expenditures and costs.

Keywords: particle swarm optimization algorithm, multi-objective particle swarm optimization algorithm, budgeting, allocation and distribution, construction project
2020 MSC: 90C29

1 Introduction

The concept of budgeting in project-based organizations requires a careful examination of specific factors and optimal performance management to forecast financial resources effectively. Budgeting constitutes the core component of an organization in achieving its objectives, as all financial activities, including revenue generation and expenditure, depend on the available budget. Therefore, the budget plays a pivotal role in organizational planning and activities, as well as at a broader national level [17].

For achieving organizational objectives and allocating resources, budgeting is recognized as an efficient and effective tool. This process facilitates the establishment of a system to control expenditures and costs [17]. Modern organizational environments are increasingly complex and chaotic compared to the past. Organizations face a vast array of decision-making variables, intensifying the need for systematic and well-founded management practices. With the advent of performance-based and program-based budgeting, budgets have become critical tools in the performance management of organizations [19].

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A significant drawback of traditional budgeting methods is the influence of individuals on increasing or decreasing the allocated budget for organizations. This often leads to misallocation, where high-priority organizations receive less budget, while low-priority organizations are allocated more [11]. If appropriate and integrated planning for budget allocation and distribution is lacking, project-based organizations and executive agencies face numerous challenges. Improper budget allocation hampers organizational operations, complicates managerial decision-making, and diminishes the ability to analyze and strategize effectively [3].

This study aims to propose an efficient method for budget distribution and allocation to various development projects within project-based organizations. Utilizing the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm as a tri-objective mathematical model, the study seeks to provide an optimal budget allocation framework. The statistical population of this research includes selected experts and specialists from Shirvan University.

2 Theoretical foundations and conceptual framework

One of the most prominent mathematical models for budgeting systems is the Charnes and Cooper model, initially employed for budgeting in the U.S. military [3, 7]. Another notable study, presented in 1994, focused on optimal allocation using a multi-criteria approach [20]. In 1996, Adel Azar designed a mathematical model for budget allocation utilizing goal programming, enabling it to adapt to uncertain and ambiguous organizational data [2]. In subsequent years, Azar extended his work by introducing a robust optimization approach for budget allocation [3].

It is evident that increased complexity and ambiguity in organizational data demand highly skilled managers and experts capable of employing advanced mathematical models and novel algorithms to overcome existing challenges. Organizations are tasked with managing multiple projects simultaneously across diverse geographical locations. Each project encompasses numerous activities, necessitating resources at varying intervals [5]. Moreover, the resources available to organizations are inherently limited, requiring managers and specialists to utilize them optimally. Consequently, efficient resource utilization hinges on optimal budget allocation, a process that faces significant hurdles when relying on traditional budgeting methods [13].

Traditional budgeting tools, such as PERT/CPM, perform allocation and planning under unconstrained conditions. However, given the complexity of today's world, these outdated methods fail to meet organizational needs and effectively achieve their objectives. There is an increasing demand for efficient and systematic planning grounded in mathematical methodologies [5].

The most powerful tool available to organizational managers for ensuring the successful execution of plans and projects is budgeting. The initial step in budget allocation is precise and structured planning. Planning is defined as the preparation, allocation, and distribution of limited resources to achieve predetermined goals within the least time and cost [8].

In a study conducted by Movahed and Rayanpour, the influential parameters in the budget allocation process for most construction projects were examined. The research utilized three methodologies: library research, online resources, and the opinions of experts in national construction projects. As a result, 13 common influential parameters were identified, each with a direct impact on project execution costs. Simulations revealed that two of these parameters—workshop waste and human resources—had the greatest influence on increasing or decreasing execution costs [14].

To reduce execution costs, Keykha [11] proposed a time management-based approach. This method identifies the optimal time to execute project activities, ensuring maximum efficiency in the shortest possible timeframe. Similarly, the soft systems methodology was employed to allocate financial resources to construction projects within the Islamic Republic of Iran Broadcasting organization. This approach aimed to achieve optimal resource allocation given budget constraints, resulting in increased employee satisfaction and productivity [18].

Identifying and analyzing the parameters that directly impact cost escalation in construction projects is of critical importance. Seboni and Ssegawa introduced a multi-criteria decision-making method to identify these factors and prevent cost overruns [16].

Numerous studies have been conducted to strike a balance between time and execution costs in construction projects. These studies propose resource allocation strategies by accounting for direct, indirect, and other project-related costs and their relationship with time. One such study highlights the experience of São Paulo in developing a cost-accounting system for public services [6].

Azadi et al. [1] employed a multi-criteria decision-making method combined with the TOPSIS model to allocate funding based on predetermined priorities. Meanwhile, in 2020, Igwe et al. introduced a cost optimization approach during the construction phase. Their study provided insights into emerging information and communication technologies and their applications in managing construction projects, with a particular focus on cost management [9].

Another key aspect of improving organizational management is leveraging the expertise of internal professionals or collaborating with external organizations related to the internal entity. Using data gathered from experts, organizations can make more informed decisions to enhance management practices [15].

2.1 Artificial neural networks

Artificial neural networks are classified into two categories: feedforward networks and recurrent networks. In feedforward networks, neuron activity propagates from the input layer toward the output layer, with all connections directed forward. In contrast, in recurrent networks, the outputs of neurons in higher layers are fed back into the inputs of neurons in earlier layers, earning them the name "recurrent networks." [14]. The type of learning employed in these networks can also serve as a criterion for their classification. Learning in some networks is supervised, while in others, it is unsupervised. One of the most widely used and effective networks is the backpropagation network. Feedforward networks generally have one or more hidden layers of neurons, meaning the neurons are organized layer by layer, and the neurons in each layer are fully connected to those in the subsequent layer. From a mathematical perspective, these networks establish and implement a mapping between input and output, or, in other words, a function [14].

2.2 Ant colony optimization algorithm

The ant colony optimization algorithm is a type of metaheuristic algorithm that uses artificial ants as agents to optimize complex problems. In this method, the proposed solution involves distributing computational resources relatively among simple agents. Artificial ants traverse the problem's graph and leave markers on it, mimicking real ants that leave traces along their paths. This behavior enables subsequent artificial ants to discover better solutions to the problem [11].

2.3 Particle swarm optimization algorithm

The particle swarm optimization (PSO) algorithm is a social search algorithm inspired by the flocking behavior of birds [4]. Initially, this algorithm was designed to identify the governing patterns behind synchronized bird flight, sudden directional changes, and the optimal reshaping of the flock. In PSO, particles flow through the search space, with their movements influenced by their experiences and knowledge as well as that of their neighbors. Consequently, the position of other particles in the swarm affects how each particle searches. This modeling of social behavior results in a search process where particles tend to move toward successful areas. Particles learn from each other and adjust their movements based on the knowledge gained, gravitating toward the best neighboring solutions.

The PSO algorithm is one of the approaches within the realm of swarm intelligence, a property of systems where agents collaborate locally, leading to collective behavior that converges near the global optimum. A key advantage of this algorithm is the absence of a centralized control mechanism. Each particle or agent has relative autonomy, moving through the solution space while interacting with others.

In 1995, PSO was introduced by Eberhart and Kennedy as a non-deterministic search method for function optimization. It was inspired by the collective movement of birds searching for food [10]. The algorithm is fundamentally based on a search and iterative process. A group of birds randomly searches for food in a space containing only a single food source. None of the birds know the exact location of the food. One effective strategy could involve following the bird closest to the food.

The movement of each particle depends on three factors:

1. The current position of the particle.
2. The best position the particle has experienced so far (Pbest).
3. The best position experienced by all particles (Gbest).

In PSO, the set of solutions obtained by the particles is referred to as the "swarm." Each solution represents a bird within the swarm, known as a particle. A fitness value is assigned to each particle, determined by the fitness function, which is equivalent to the objective function being optimized. The particle's movement direction is determined by a velocity vector. Based on its personal experience and the experiences of others, the particle moves toward the optimal destination.

One of the key benefits of this algorithm is that it does not generate new solutions based on previous ones. The operational framework of PSO is illustrated in the block diagram in Figure 1. The algorithm begins with a set of random solutions. Subsequently, the fitness function evaluates each particle's position to determine the best position for both individual particles and the entire swarm. In the next step, by updating the position and velocity of each particle, the search for the global optimum solution continues.

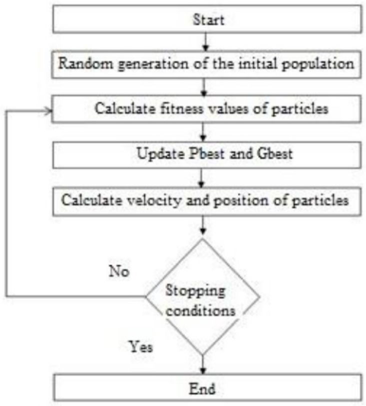

Figure 1: PSO algorithm

The PSO algorithm operates for a D-dimensional problem as follows: the position of the iii-th particle in the initial population is represented as $X_i = (x_{i1}, x_{i2}, ..., x_{iD})^T$ and the velocity of this particle is denoted by $V_i = (v_{i1}, v_{i2}, ..., v_{iD})^T$. If the iteration in the PSO algorithm is denoted by the variable N, the equations are expressed as:

$$V_{id}^{n+1} = V_{id}^n + C_1 r_1^n (pbest_{id}^n - X_{id}^n) + C_2 r_2^n (gbest_d^n - X_{id}^n) \tag{2.1}$$

$$X_{id}^{n+1} = X_{id}^n + V_{id}^{n+1} \tag{2.2}$$

In the above equations, C_1 and C_2 are constant and positive coefficients, typically selected within the range of 1.5 to 2 depending on the problem. The parameters r_1 and r_2 are random numbers uniformly distributed within the interval (0&1).

Usually, the parameter V_{id}^{n+1}, known as the inertia weight, is introduced for the equation. Thus, the equation V_{id}^{n+1} is modified as follows:

$$V_{id}^{n+1} = WV_{id}^n + C_1 r_1^n (pbest_{id}^n - X_{id}^n) + C_2 r_2^n (gbest_d^n - X_{id}^n) \tag{2.3}$$

The purpose of using the inertia weight is to control the impact of previous velocities to achieve convergence of the algorithm. This parameter creates a trade-off between local and global exploration. The inertia weight is dynamically selected; a larger value increases global exploration, while a smaller value enhances local search.

2.4 Multi-objective particle swarm optimization algorithm

The multi-objective particle swarm optimization (MOPSO) algorithm is a generalized version of the PSO algorithm [12]. MOPSO is used for problems with multi-objective functions. In this algorithm, a new concept called the archive, also known as the hall of fame, is introduced. The most critical step in the MOPSO algorithm is identifying the global best solution and the best personal experience of each particle. To determine the particle's movement, a member of the archive is chosen as the leader. These leaders must be selected from the archive. While the PSO algorithm uses GbestGbestGbest, the MOPSO algorithm selects one of the archive members. The personal best experience is updated as follows:

1. If the new position of the particle dominates the previous experience, the new position replaces the best memory. In other words:
$$pbest_i^{n+1} = X_i^{n+1} \tag{2.4}$$
2. If the best memory dominates the new position, no change occurs:
$$pbest_i^n = pbest_i^{n+1} \tag{2.5}$$

If neither of the above conditions is met, one of the two vectors is randomly chosen as the best position. The advantages of using PSO are as fallow:

- Population-based approach: The algorithm's reliance on a population reduces the likelihood of getting trapped in local minima compared to other algorithms.
- Probabilistic rules: The algorithm's mechanism is based on probabilistic rather than deterministic rules. Thus, PSO is a stochastic optimization algorithm capable of exploring uncertain and complex regions, providing more flexibility and resilience compared to other methods.
- Handling non-differentiable objective functions: PSO operates with the outcomes (objective function values) to guide the search in the solution space.
- Independence from the initial population: The quality of the proposed solution does not depend on the initial population. Regardless of the starting point in the search space, the algorithm converges to the optimal solution.
- Flexibility in balancing exploration and exploitation: PSO allows for control over local and global exploration in the search space. This unique property helps overcome premature convergence and enhances search capacity, distinguishing PSO from genetic algorithms (GA) and other heuristic methods.

3 Research methodology

This article aims to present an efficient model for allocating and distributing budgets to construction projects at Shirvan University of Applied Science and Technology using the multi-objective particle swarm optimization (MOPSO) algorithm. Accordingly, a mathematical model is proposed for budget allocation to construction projects, aiming to maximize project utility, expert preferences, and project performance quality. In this context, the study employs the MOPSO algorithm as a multi-objective mathematical model capable of determining the optimal allocation of budgets within a multi-objective framework. The reason for choosing this algorithm lies in its status as one of the most up-to-date and effective metaheuristic algorithms compared to other methods, offering faster convergence rates and robust performance, as highlighted in the previous section. The results of the model's implementation include achieving the primary overarching goal: "providing an efficient quantitative model for budget allocation and distribution to construction projects." Below, the proposed model is described in detail.

The mathematical model for multi-objective budgeting in this study is expressed as follows:

$$
\begin{aligned}
&\max Z_1 = \sum_i \sum_j b_i x_{ij} d_{ij} \\
&\max Z_2 = \sum_i \sum_j m_i x_{ij} d_{ij} \\
&\max Z_3 = \sum_i \sum_j q_i x_{ij} d_{ij} \\
&\sum_i x_{ij} \leq F_j \qquad \forall j \\
&\sum_j x_{ij} \leq t_i \qquad \forall i \\
&P \min_{ij} \leq x_{ij} \qquad \forall i, j \\
&\quad x_{ij} \leq P \max_{ij} \qquad \forall i, j
\end{aligned}
\tag{3.1}
$$

In this model, the number of i projects is considered over a time period of j periods. In other words, a total of 4 construction projects are considered over 4 seasons of the year, with a budget allocated to each project in each season. The allocation of the budget to each project is conditional upon meeting the following objectives:

1. Maximizing the utility of the project
2. Maximizing the satisfaction of individuals, including stakeholders and university students
3. Maximizing the performance of the projects

The block diagram of the proposed method is shown in Figure 2. This block diagram consists of several components, which include: identifying the budget allocation parameters, introducing the indicators, introducing the decision variables for allocation and distribution of the budget, introducing the model parameters, optimization using a multi-objective particle swarm optimization algorithm, and stopping criteria. The proposed method is explained in detail below.

3.1 Introduction of practical tools

MATLAB software is a programming environment for performing numerical computations, and it is used in this study for optimizing the budget allocation problem. In this research, MATLAB 2014a version is used to solve the multi-objective optimization model. Additionally, for simulating the proposed method, a CPU with specifications of Intel Core i7-6700HQ, an NVIDIA GEFORCE GTX 950M graphics card, a GPU, and 8 GB of memory are utilized.

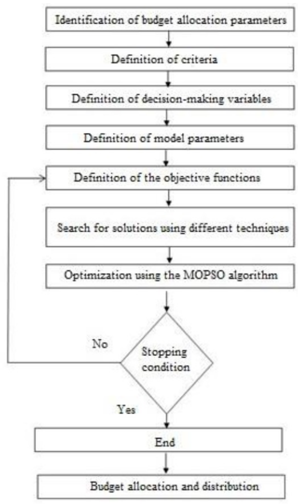

Figure 2: Block diagram of the proposed method

The model's indices are as follows:

i: Represents the project, with a total of 4 projects (i = 1, 2, 3, 4)

j: Represents the time period for project execution, with a total of 4 time periods (j = 1, 2, 3, 4)

The decision variables are defined as follows:

x_{ij}: The amount of budget allocated to project i during time period j

d_{ij}: A binary variable where 1 indicates budget allocation to project i during time period j, and 0 indicates no budget allocation to project i during time period j

The model parameters are as follows:

F_j: The maximum available budget in time period j

b_i: The benefit or utility of project i

q_i: The qualitative value of project i

t_i: The maximum total budget allocated to project i across all time periods

m_i: The acceptability of project i from the perspective of stakeholders

$Pmin_{ij}$: The minimum budget required to be allocated to project i during time period j

$Pmax_{ij}$: The maximum budget that can be allocated to project i during time period j

3.2 Objective function structure

In this study, three objective functions are defined to achieve optimal budget allocation. Each objective function is explained below:

1. First Objective Function (Project Utility):
   The first objective function focuses on the utility or desirability of each project. The mathematical relationship is given as:
   $$\max Z_1 = \sum_i \sum_j b_i x_{ij} d_{ij}$$
2. Second Objective Function (Project Acceptance):
   The second objective function measures the acceptance of each project from the perspective of various stakeholders, including university faculty and students. The relationship is expressed as:
   $$\max Z_2 = \sum_i \sum_j m_i x_{ij} d_{ij}$$
3. Third Objective Function (Project Performance):
   The third objective function aims to maximize project performance. Its mathematical representation is:
   $$\max Z_3 = \sum_i \sum_j q_i x_{ij} d_{ij}$$

3.3 Constraint structure

For the proposed model, four constraints are considered, each ensuring a specific condition for budget allocation and contributing to the efficient distribution of funds to each project:

3.3.1 First constraint (available budget per project and period)

This constraint ensures that the allocated budget for each project does not exceed the available budget during its execution period. In each of the four execution periods, the budget allocated to a project must be less than or equal to the maximum budget available for that project in the given period:

$$\sum_i x_{ij} \leq F_j \qquad \forall j$$

where F_j represents the maximum available budget for period j.

3.3.2 Second constraint (cumulative budget allocation)

This constraint ensures that the total budget allocated to a project across all periods does not exceed the overall maximum budget allocated to the project:

$$\sum_j x_{ij} \leq t_i \qquad \forall i$$

where t_i represents the maximum total budget for project i.

3.3.3 Third constraint (minimum budget threshold)

This constraint ensures that the allocated budget for project ii in execution period j meets the minimum budget requirement. In other words, in each period, the budget allocated to a project must be greater than or equal to the specified minimum threshold:

$$Pmin_{ij} \leq x_{ij} \qquad \forall i, j$$

where $Pmin_{ij}$ is the minimum budget required for project i in period j.

3.3.4 Fourth constraint (maximum budget threshold)

This constraint ensures that the budget allocated to project ii in execution period jj does not exceed the maximum allowable budget. Thus, the allocated budget for each project in each period must be less than or equal to the specified maximum threshold:

$$x_{ij} \leq Pmax_{ij} \qquad \forall i, j$$

where $Pmax_{ij}$ is the maximum budget allowed for project i in period j.

4 Application of multi-objective particle swarm optimization algorithm for budget

In project-based organizations, allocating and distributing budgets require consideration of various factors such as social accountability and others. The data and information used for budget allocation in this research were collected from Shirvan University of Applied Science and Technology.

The data and parameters of the proposed model were used to allocate and distribute funds across four development projects over a one-year period (comprising four seasons). The four projects used for simulating the proposed model are as follows:

- **P1:** New Building for the Law Department
- **P2:** New Building for the Architecture Department
- **P3:** New Building for the Accounting Department
- **P4:** New Building for the Beekeeping Department

In each season of the year, a budget is allocated to each development project. The parameters and data of the model are listed in the following tables. The abbreviations used in the tables are as follows:

- **j = 1**: Spring
- **j = 2:** Summer
- **j = 3:** Autumn
- **j = 4:** Winter

Table 1 presents the information obtained from Shirvan University of Applied Science and Technology. As stated earlier, the costs are considered in millions of rials. For example, the value "0.95" in Table 1 represents a budget of 950 million rials.

Table 1: Initial Input Parameters of the Proposed Model

Parameters	b_i	q_i	m_i	t_i
P1	0.95	0.95	1	0.3
P2	0.88	0.93	4	0.25
P3	0.79	0.90	3	0.25
P4	0.90	0.98	2	0.2

In this table, the m_i parameter, representing the acceptability of the project, is a value defined by the project stakeholders and indicates the importance of each project, with an importance scale ranging from 1 to 4. Similarly, the q_i parameter represents the qualitative value of the project, ranging from 0 to 1. The b_i parameter indicates the utility of the project, also ranging from 0 to 1, while the t_i parameter represents the maximum budget that can be allocated to each project.

Table 2: Initial Input Parameters of the Proposed Model

Time Periods	**j=1**	**j=2**	**j=3**	**j=4**
F_j	0.45	0.30	1.55	0.95

In Table 2, each number is between 0 and 1, and for example, the number 0.45 represents 450 million Tomans. The total budget allocated for all 4 projects is one million Tomans. This budget is further specified in Tables 3 and 4 for each project and each time period.

Table 3: Maximum Budget Allocated to Each Project in Different Time Periods ($Pmax_{ij}$)

Time Periods	**j=1**	**j=2**	**j=3**	**j=4**
P1	1.00	0.50	0.25	0.25
P2	1.50	1.00	0.75	0.25
P3	1.00	1.00	0.30	0.20
P4	1.00	0.50	0.25	0.25

In Table 3, the maximum budget allocated to project i during time period j is represented as $Pmax_{ij}$. For example, for project P1 in time period j=1, a budget of 100 million (1.00) is allocated. Similarly, the allocated budget for all projects across different time periods is listed.

Table 4: Minimum Budget Allocated to Each Project in Different Time Periods ($Pmin_{ij}$)

Time Periods	j=1	j=2	j=3	j=4
P1	0.50	0.20	0.00	0.10
P2	1.00	0.50	0.40	0.00
P3	0.30	0.40	0.10	0.00
P4	0.75	0.40	0.00	0.20

In Table 4, the minimum budget allocated to project i during time period j is represented as $Pmin_{ij}$. As an example, for project P1 in time period j=1, a budget of 50 million (0.50) is allocated. Similarly, the minimum allocated budget for all projects across different time periods is listed.

5 Analysis of results and evaluation

This section provides an analysis of the results obtained from the proposed model and its solution using the MOSOP algorithm. Table 5 lists the values of the $dijd_{ij}dij$ variable for the proposed method, indicating the budget allocation status for each project across the four time periods.

Table 5: Budget Allocation Status for Each Project

Time Periods	j=1	j=2	j=3	j=4
Projects				
$P1P_1P1$	1	1	1	1
$P2P_2P2$	1	1	1	0
$P3P_3P3$	1	1	1	0
$P4P_4P4$	1	0	1	1

In this table, the value "1" indicates that the budget is allocated to a project during a specific period, whereas "0" indicates no allocation. For example, project P4 received funding only in the first, second, and fourth periods, while project P1 received funding throughout all periods.

Table 6 lists the values of the X_{ij} parameter obtained from the proposed method, representing the amount of budget allocated to project iii during period j.

Table 6: Budget Allocation Amount for Each Project Using the Proposed Method

Time Periods	j=1	j=2	j=3	j=4
Projects				
$P1P_1P1$	0.897	0.449	0.224	0.022
$P2P_2P2$	0.134	0.890	0.673	0.221
$P3P_3P3$	0.890	0.871	0.269	0.179
$P4P_4P4$	0.895	0.449	0.221	0.224

As shown in Table 6, for instance, project P1 was allocated a budget of 89.7 million tomans (0.0897) during the time period j=1. Similarly, the allocated budgets for other projects across various time periods are listed in the table.

In the following, the results obtained from the proposed method for different numbers of iterations are presented. The tables below list the results for 200, 400, and 500 iterations. In other words, the algorithm for the proposed method has been executed with a specified number of iterations, and the results are shown in the following tables. As can be seen from these tables, the proposed method with 500 iterations achieved the best possible result. After that, the 400-iteration count followed by the 200-iteration count produced progressively less optimal results. Using 500 iterations allows the particles to have better weights compared to the 400 and 200 iterations, and the algorithm performs more accurately in budget allocation.

5.1 Comparison with other methods

In this section, the proposed method is compared with the Artificial Neural Network (ANN) method [16] and the Ant Colony Optimization (ACO) algorithm [17]. The figures below display the budget allocation for four projects

Table 7: Budget Allocation Results Using the Proposed Method with 200 Iterations

Time Periods	**j=1**	**j=2**	**j=3**	**j=4**
99 P1	0.99	0.0491	0.0249	0.025
P2	0.15	0.994	0.0748	0.0248
P3	0.99	0.996	0.299	0.0199
P4	0.98	0.0488	0.0245	0.024

Table 8: Budget Allocation Results Using the Proposed Method with 400 Iterations

Time Periods	**j=1**	**j=2**	**j=3**	**j=4**
99 P1	0.993	0.0497	0.0248	0.025
P2	1.490	0.993	0.0745	0.0249
P3	0.990	0.993	0.298	0.0199
P4	0.991	0.0497	0.0248	0.0234

Table 9: Budget Allocation Results Using the Proposed Method with 500 Iterations

Time Periods	**j=1**	**j=2**	**j=3**	**j=4**
99 P1	0.897	0.0449	0.0224	0.022
P2	0.134	0.089	0.0673	0.0221
P3	0.890	0.871	0.269	0.0179
P4	0.895	0.0449	0.0221	0.0224

using the proposed method alongside the other methods, with 500 iterations. Figures 3 to 6 show the budget allocated to four projects for the different time periods (j1, j2, j3, and j4). As observed from the results, the proposed method outperforms the ANN and ACO methods in terms of efficiency.

As shown in Figure 3, for example, in the case of project P1 during time period j=1, the budget allocated is 0.897 million (or 89.7 million IRR). The same budget allocations are presented for the other projects across different time periods. Figure 4 demonstrates that the proposed method performs better than the other two algorithms, with the budget allocation for project P1 in time period j=1 being 0.449 (or 44.9 million IRR) for the proposed method. In contrast, the ANN and ACO algorithms allocated 0.352 and 0.426, respectively. Similar budget allocations for other projects and time periods are shown, illustrating the superior performance of the proposed method over the other approaches.

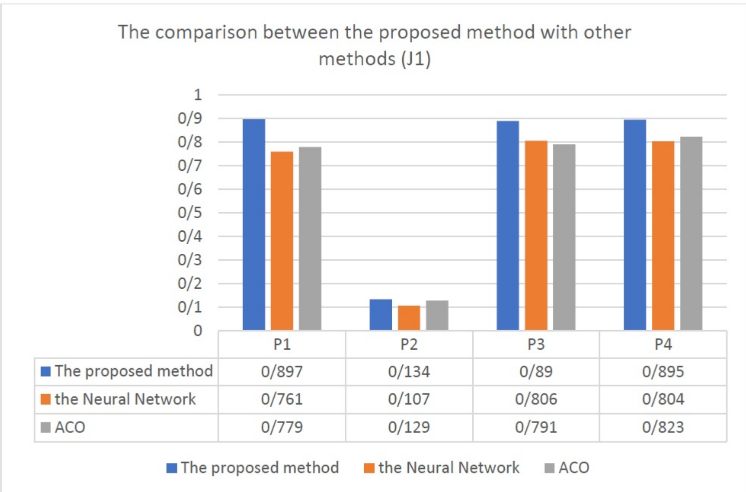

Figure 3: Evaluation of the proposed method with other methods (j1)

6 Conclusion

In this paper, a three-objective budget allocation model with four constraints was presented to achieve efficient budget allocation and distribution. The proposed model is designed for the allocation of funds to the infrastructure projects of the University of Applied Sciences of Shirvan. Using the Multi-Objective Particle Swarm Optimization

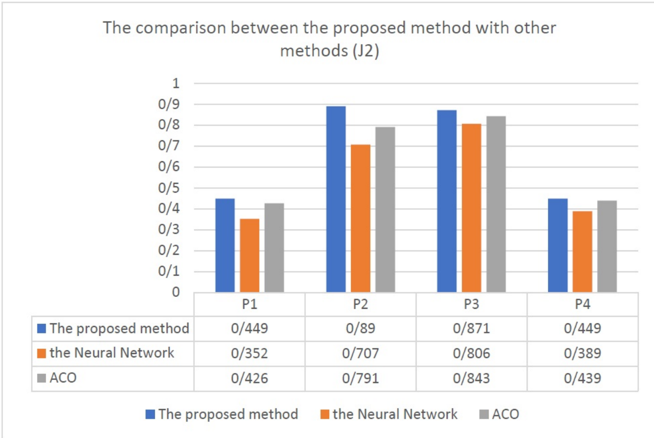

Figure 4: Evaluation of the proposed method with other methods (j2)

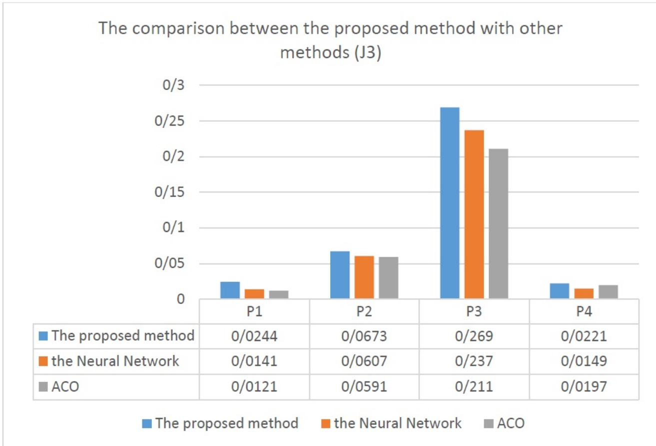

Figure 5: Evaluation of the proposed method with other methods (j3)

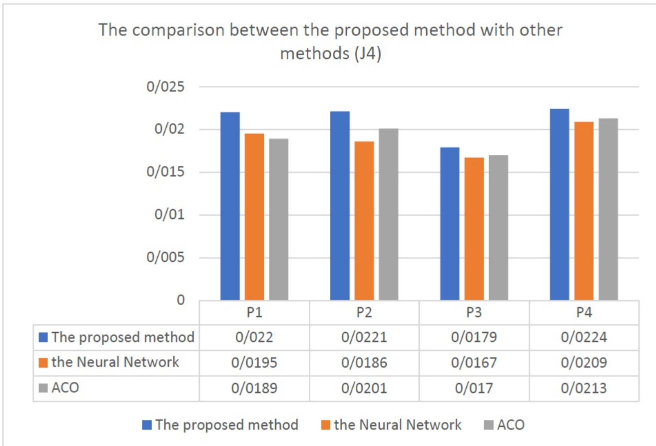

Figure 6: Evaluation of the proposed method with other methods (j4)

(MOSOP) algorithm, the objectives of this model include maximizing the available budget for each time period, maximizing the budget allocated to each defined project, and evaluating the benefit or advantage of each project. Based on these objectives, the best budget allocation for each project across the defined time periods is determined. Finally, the proposed budgeting model was evaluated and compared with two methods: Artificial Neural Networks (ANN) and Ant Colony Optimization (ACO). The results from solving the proposed model demonstrate its superiority in budget allocation and distribution, as further analyzed in the results section, where the proposed method is compared with the artificial neural networks and ant colony optimization algorithm.

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