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Finance-based Scheduling for Cash-flow Management of Maintenance Portfolios: Multi-objective Optimization Approach

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ABSTRACT

Bridge agencies are often challenged to develop maintenance programs under given budgets. Numerous studies developed budget-allocation models for maintenance programs during defined planning horizons of multiple fiscal years while totally ignoring the crucial aspect of cash flow. The payment schedules (both timing and amount) for contractors might indicate agencies' cash needs that exceed the available budgets during certain fiscal years, which create cash flow problems. While numerous finance-based scheduling (FBS) models were developed to manage cash flow for contractors, this function was totally overlooked for portfolio owners. Thus, this research reintroduces the FBS from the perspective of portfolio owners. A FBS model is developed to schedule the activities of the portfolio projects, utilize the schedules to define the payment schedules of projects' contractors, calculate the agencies' cash needs during the fiscal years, and utilize the multi-objective optimization algorithms of NSGA-II, SPEA-II, and MOPSO to optimize the projects' schedules to achieve a balance between the cash needs during the fiscal years and the available budgets. The anticipated extensions in projects' completion represent the conflicting objectives. Finally, the optimized schedules make the contractors' payment schedules affordable by the agencies' budgets, which help to complete projects successfully and achieve the programs' strategic goals.

1. Introduction

1.1 Research Background

Bridges constitute a major component in the highway network, which require large capital investments for the construction and maintenance. The continuously increasing traffic volumes have resulted in higher loads on bridges than those considered in design. Consequently, many bridges exhibited deficiencies including reduced capacity, degraded functional performance, and restricted vehicle loads. These deficiencies are completely attributable to inadequate maintenance. Existing damages on bridges coupled with high traffic loads and severe environmental conditions cause accelerated deterioration and require urgent maintenance actions. The large number of bridges and

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the high costs of maintenance called for the development of effective approaches for maintenance planning and management.

Bridge management tackles all activities throughout the entire life span starting from construction until replacement to ensure safety and functionality of bridges. A bridge management system is defined as "a tool for assisting highway and bridge management agencies in their choice of optimum improvements to the bridge network that are consistent with the agency's policies, long term objectives and budgetary constraints" [1]. The choice of optimum improvements involves assigning priority for maintenance needs, planning activities for carrying out the maintenance, and optimizing the life-cycle cost of bridges. One of the fundamental functions of bridge management constitutes decision-making regarding the allocation of budget to the maintenance operations. Bridge management systems enable highway and bridge agencies to operate within budgetary constraints while achieving bridge performance goals [2].

Effective bridge management employs optimization algorithms to develop optimal maintenance and repair (M&R) programs subject to budget constraints. Typically, optimization problems are formulated to minimize cost functions subject to budgetary constraints in addition to other constraints including bridge reliability thresholds, and bridge elements' conditions. The cost functions include life-cycle cost components of the bridge construction and maintenance in addition to the costs of the user throughout the bridge service life. Thus, the required input to the optimization involves the cost estimates of alternative maintenance strategies and their effectiveness as indicated by the period of service between two successive strategies. The optimization is performed considering a number of bridges within a defined planning horizon of multiple fiscal years. The outcome represents an optimal maintenance program, which enables highway and bridge agencies to make decisions regarding the budget allocation and the selection of maintenance strategies.

There are two primary types of bridge management systems: network-level or project-level systems. While the project-level systems concentrate on the selection of repair techniques for individual bridges and their parts, the network-level systems deal with the prioritization of bridges for consideration in a planned maintenance, repair, and rehabilitation program. The allocation of limited budget is one of the aspects that is predominantly addressed at the network level [3,4]. Unfortunately, the developed models in the literature perform budget allocation while totally ignoring the crucial and closely-related aspect of cash flow. Cash flow problems are potentially aggravated by taking into account the fact that most of the maintenance projects are outsourced and the agencies have contractual obligations to make payments to contractors of specific amounts at specific times. While the budget allocation ensures that funds are available during the planning horizon of multiple fiscal years to cover the overall maintenance costs, the operational plans and schedules of executing the maintenance works might indicate contractors' payments during some fiscal years that exceed the budgets available during these fiscal years. If these circumstances arise, the agencies will definitely experience negative cash flow which can negatively affect the progress of work and compromise the success of the programs during the execution of the maintenance works.

One remarkable study by Mohammadi *et al.,* [5] offered a model for decision-making that integrated lean construction concepts into traditional formalized road maintenance planning and scheduling, allowing for a reduction of non-value-adding tasks. During the execution phase, the chosen interventions are assigned, which is typically accomplished through outsourcing, and the interventions are implemented using operational plans and work scheduling. Mohammadi *et al.,* [5] reported that the focal aspects of the execution stage include the cash-flow management, especially when most of the work is outsourced to contractors, as well as the other operational requirements. Mohammadi *et al.,* [5] emphasized that these aspects should be adequately addressed, otherwise the success of the M&R program is potentially compromised. Furthermore, Mohammadi *et al.,* [5] stated that there won't be much flexibility in the operational plans to accommodate the necessary changes and modifications during the execution phase because the M&R plans were generated in a separate phase, possibly by different teams, and based on longer planning periods. In order to minimize issues and wastes in the construction phase, Kordestani *et al.,* [6] recommended that the viewpoints of the operating team and other concerns should be taken into account during the planning stage. Therefore, the current research addresses the problem of setting M&R plans without addressing the projects' cash flow. Despite finance-based scheduling (FBS) models were developed in the literature to perform the management of cash flow for contractors, portfolio owners were totally overlooked. This research reintroduces the FBS method to perform the cash flow management for the owners of maintenance portfolios.

The objective of this study is to help portfolio owners manage their cash flow. For being sure that the allocated budgets during fiscal years are adequate for owners to timely make contractors' payments of the projects selected in the maintenance programs, cash flow management is crucial. Specifically, this study proposes a FBS model to schedule the activities of the portfolio projects, utilize the schedules to define the payment schedules of the projects' contractors, calculate the agencies' cash needs during the fiscal years, and use the multi-objective optimization algorithms to optimize the projects' schedules (start times of projects and their activities) to achieve a balance between the agencies' cash needs, which represent the cash-out, during the fiscal years and the allocated budgets, which represent the cash-in. Practically, the optimized schedules make the contractors' payment schedules affordable by the agencies' budgets.

The sections of the paper are organized as follows: (1) Relevant literature in the areas of budget allocation and cash flow management is reviewed in the remaining part of section one. At the end of the literature review, the research gap and significance are highlighted and the study objective is clearly stated. (2) The methodology is presented in section two including the cash flow model, formulation of the optimization model, multi-objective optimization algorithms, representation system, and special serial-schedule heuristic. (3) In section three of results and discussions, an illustrative case portfolio is presented and solved using the multi-objective optimization algorithms. (4) In section four of benchmarking, a rigorous comparison between the multi-objective optimization algorithms is conducted. The two measures of elite Pareto front and set coverage are used to evaluate the quality of the Pareto fronts of the multi-objective optimization algorithms. In addition, four performance metrics are introduced and used to compare the performance of the multi-objective algorithms. Five more case portfolios of different projects' sizes are solved and the results of the experiments are presented and discussed. (5) In section five, the practical implications of the proposed method of balancing the agencies' cash needs during the fiscal years and the available budgets during fiscal years are discussed. (6) Finally, the drawn conclusions of the study and the suggestions for future research are provided.

1.2 Literature Review

This section reviews the studies conducted in the two fields of budget allocation of bridge maintenance projects, and cash flow management of construction projects.

1.2.1 Budget Allocation

Several optimization strategies have been developed by researchers to attain the optimal budget allocation for asset maintenance. Multi-attribute utility theory was used by Gharaibeh *et al.,* [7] to establish a method for allocating funds to asset classes. Using this method, decision makers can evaluate trade-offs between asset classes while taking funding transfers into account. Empirical asset condition indexes were used by Mrawira and Amador [8] and Kuhn [9] to solve problems of multiple assets and single objective. In order to optimally allocate budget to assets at the network-level, the National Cooperative Highway Research Program [10] established a utility maximization approach which is based on priority weights. The concept and structure of a two-stage procedure to carry out a trade-off analysis, for multiple assets at multiple levels, were introduced by Fwa and Farhan [11]. Using a bottom-up approach, Yeo *et al.,* [12] addressed a budget-allocation problem for infrastructure systems of heterogeneous nature with a definite planning horizon. A methodology for allocating money across several assets while accounting for structural, functional, and environmental performance factors was proposed by Dehghani *et al.,* [13]. A methodological approach for resource allocation for multiple assets based on the performance was presented by Porras-Alvarado *et al.,* [14]. Utility functions were employed to fairly allocate resources for multiple asset classes. Subsequently, trade-off analyses between various allocation scenarios were carried out using social welfare and collective utility functions. For problems with multi-facility deteriorating infrastructure systems, Shi *et al.,* [15] presented an integrated budget allocation and preventative maintenance optimization model. In order to reduce the overall carbon emissions of bridge networks that have maintenance budget constraints, Xu and Guo [16] designed a maintenance strategy for bridges that is based on conditions. To assess the effects of budget levels on maintenance schedules and overall carbon emissions, sensitivity analyses were carried out. In order to optimize bridge performance while adhering to available annual budgets, Ghafoori *et al.,* [17] proposed a system that employs machine learning to forecast the condition of concrete bridge components and a binary linear programming optimization technique to determine the optimal selection of maintenance actions and their timing. In order to enhance and facilitate the bridge management system, Mohammadi *et al.*, [18] provided a thorough approach as an advanced asset management system that makes use of data from bridge information modeling. A decision support system is integrated into the bridge management system in order to rate the feasible remedies and produce more objective decisions for the optimal allocation of funds and remedial planning.

As discussed above, the developed models in the literature have consistently been performing budget allocation while totally ignoring the crucial and closely related aspect representing the project cash flow. The construction phase involves the assignments of the selected maintenance projects and the implementation of the maintenance strategies through operational plans and scheduling tasks. Focal aspect during the construction stage represents the cash flow, especially when most of the maintenance projects are being outsourced to contractors. Therefore, cash flow should be carefully planned and controlled, otherwise the success of the M&R programs can potentially be compromised.

1.2.2 Cash Flow Management

Numerous research efforts have been exerted to predict, plan, and control cash flow. A model to maximize schedule robustness while minimizing project cost with the integration of cash flow has been carried out by Cao *et al.,* [19]. A sensitivity analysis was conducted by Tavakolan and Nikoukar [20] to investigate the impact of modifications to the characteristics of cash flow on the project duration versus financing cost trade-off. Dabirian *et al.,* [21] created a model to predict, plan, and manage various policies, such as prepayment and payment delay, by detecting the feedback loops in cash flow. A simulation-based methodology was developed by Andalib *et al.,* [22] to predict project cash flow taking into account the intertemporal relationship between subsequent progress payments and the history of the owners' payment in past projects. A methodology that generates cash flow predictions to reduce financing costs while considering various financing options and non-extended work schedules was provided by Alavipour and Arditi [23]. Singularity functions were utilized by Su and Lucko [24] to accurately compute project cash flow balances. An automated technique was presented by Lee *et al.,* [25] to address the uncertainties surrounding the costs and durations of the activities and enhance the reliability of project cash flow analysis. An IT system was established by Motawa and Kaka [26] to assist all supply chain participants in selecting the most suitable cash flow and payment method. A mathematical method, that is fuzzy and entropy-based, was used by Tang *et al.,* [27] to handle the objective function weighting problem in the models of cash flow. Lee *et al.*, [28] established the causal connection between the causes and effects of nonpayment using a decision-making trial and evaluation laboratory technique. The main contributing elements include the paymaster's poor financial management, the local way of life and culture, mistakes in documents, terms of contracts, and differences in the estimation of completed work. Cash flow problem was one of the key repercussions. It is remarkable that, all of the examined research efforts in this section considered the cash flow exclusively from contractors' perspective.

Few studies were carried out in the literature considering the cash flow from the owners' (agencies') perspective. An analytical and decision support framework for managing cash flow and payments in construction projects was developed by Dorrah and McCabe [29] for a variety of stakeholders, including owners, contractors, and subcontractors. The framework incorporates game theory and agent-based modeling and simulation to analyze the collaborative decision-making process, the cash flow and payment system, while considering the individual and collective features of stakeholders. Governments are given a tool provided by Shalaby and Ezeldin [30] to choose work packages for large-scale projects supported by the "Results-Based-Finance" mechanism in a way that improves project cash flow in terms of early cash-in collection. Based on genetic algorithms and case-based reasoning, Liang *et al.,* [31] developed a cash flow model to forecast the expenditures of transportation agencies' design-build projects. An agent-based simulation model was provided by Farshchian *et al.,* [32] to mimic budget allocation and how it affects the progress of construction projects in an owner's portfolio. A dynamic threshold cash flow based structural model was used by Huang *et al.,* [33] to assist owners in determining each construction contractor's credit quality score during the prequalification stage. Jarrah *et al.,* [34] examined TxDoT projects during the period from 2001 to 2003 in order to develop mathematical models that depict the monthly payments made to contractors. An owner who has to manage the budget for several projects has to estimate the contractor payments for the upcoming months in order to plan for them. It is remarkable that, none of these studies balances the agency's cash-in and cash-out amounts during fiscal years.

FBS method schedules projects' activities during the projects' individual billing periods under the limited cash-in while minimizing extensions in projects completion. Cash-in is available during a given billing period through two sources: (1) the money received for activities completed and billed during earlier billing periods; and (2) the external funds procured through the lines of credit with preset credit limits. FBS method balances the contractors' cash-out representing the project direct and indirect costs with the cash-in available during the individual billing periods. FBS method fulfils the credit-limit constraints imposed on the amounts of the negative overdraft values, which are realized as of the ends of the billing periods. Since FBS was originally introduced by Elazouni and Gab-Allah [35], many research efforts in the literature developed models to solve FBS problems [36-41]. However, the FBS models developed in the literature adopt the cash flow exclusively from the perspective of the contractors.

The cash flow model of the agencies is completely different from that of the contractors in terms of components and structure. The agencies' cash-out component represents the contractors' payments, which happen at discrete dates as opposed to the cash-out in FBS, which happens in continuous mode. The agencies' cash-in component represents the predetermined budget amount available during each fiscal year within the planning horizon as opposed to the cash-in in FBS, which is determined based on the activities completed and billed during earlier billing periods. The agencies' cash flow structure is composed of the planning horizons of multiple fiscal years as opposed to the short billing periods in FBS.

The main research gap in this study is that the bridge maintenance agencies set bridge M&R programs while completely ignoring the crucial aspect of cash flow. Given the fact that most of the maintenance projects are outsourced, cash flow problems could delay progress and potentially compromise the success of the M&R programs. Another research gap is that numerous FBS models were developed to manage cash flow for contractors while totally overlooking the cash flow of portfolio owners. Thus, the objective of this research is to reintroduce FBS to effectively manage the cash flow for portfolio owners. A multi-objective optimization method is employed to optimize the schedules (start times of projects' starts activities and the remaining activities) of projects in portfolios to achieve a balance between the agencies' cash needs during the fiscal years and the allocated budgets. The employed multi-objective scheduling optimization algorithms minimize the anticipated extensions in the completion of the individual projects. The optimization output presents to the decision maker a Pareto front with a set of solutions, each solution involves the optimized schedules of the individual projects. Thus, the Pareto fronts facilitate decision-making regarding the selection of the most appropriate solution based on the set priority of projects for early completion.

2. Methodology

2.1 Cash Flow Model

There are multiple projects in a portfolio that make up the current scheduling problem. The activities of the project have a single mode of operation and cannot be stopped once it has begun. The payments made to contractors represent the agency's cash-out and are determined by the contract prices of the activities. It is assumed that the price of activity a_i is distributed uniformly over the activity's duration and has a rate of c_i per day.

Projects in portfolios are typically assigned to various contractors with varying start dates and payment terms. Bills from contractors are turned in at the last day of each billing period. The project's start date as well as the start date of the first billing period are indicated by the start time of the project's start activity. $Y_{i,b}$ is the contractor's invoiced amount for the portion of activity a_i that falls in billing period b. This amount is determined by applying one of the four cases in Eq. (1), depending on the overlap between the activity duration and the billing period, as depicted in Figure 1.

$$Y_{i,b} = \sum_{s_i}^{F_b} c_i \qquad F_b \geq s_i \geq S_b \text{ and } f_i \geq F_b \tag{1a}$$

$$Y_{i,b} = \sum_{S_b}^{f_i} c_i \qquad s_i < S_b \text{ and } S_b \leq f_i < F_b \tag{1b}$$

$$Y_{i,b} = \sum_{s_i}^{f_i} c_i \qquad s_i \geq S_b \text{ and } f_i < F_b \tag{1c}$$

$$Y_{i,b} = \sum_{S_b}^{F_b} c_i \qquad s_i < S_b \text{ and } f_i \geq F_b \tag{1d}$$

Where; c_i is activity's a_i price per day; s_i and f_i are activity's a_i start and finish dates respectively; and S_b and F_b are the start and end dates of billing period b respectively. Eq. (1) computes $Y_{i,b}$ for every billing period based on s_i and f_i in comparison to S_b and F_b as shown in Figure 1.

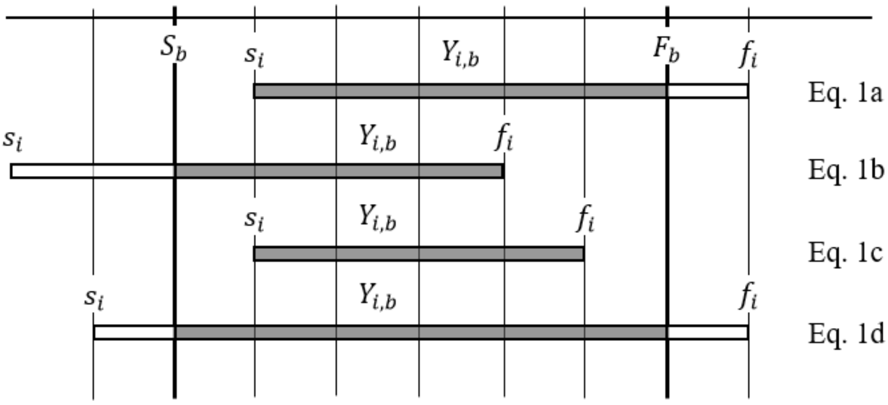

Fig. 1. The earned cash amounts during the billing period b

The sum of the billed amounts of activities n_b, or portions of them, that are completed within the billing period b as in Eq. (2), determines the contractor's billed amount of Y_b during billing period b.

$$Y_b = \sum_{i=1}^{n_b} Y_{i,b} \tag{2}$$

As in Eq. (3), the contractor's payment in project j, $E_{j,b}$ is computed using the billed amount Y_b, and a reduction factor r that jointly accounts for the advance payment payback and the retainage percentage. One period after the bill is submitted, the contractor receives the payment.

$$E_{j,b} = Y_b * [1 - r] \tag{3}$$

The first term in Eq. (4) indicates how to determine the sum O_t of contractors' payments E_j of m_t projects that are underway throughout fiscal year t. The V_t parameter in Eq. (4) is the sum of all projects' advance payments and retained amounts' repayments that take place during fiscal year t. The agency's cash-out for fiscal year t is represented by O_t in Eq. (4).

$$O_t = \sum_{j=1}^{m_t} E_j + V_t \tag{4}$$

The agency's budget, or cash-in, is linked to a certain planning horizon consisting of several fiscal years. The available budget for a given fiscal year t is represented by I_t, which may or may not remain constant for each fiscal year included in the planning horizon. It may become necessary to shift the start times of different activities as the scheduling process moves forward year after year in order to maintain the sought balance between the budgeted amount I_t and the cash-out amount O_t. There may be instances where the budgeted amount available for a particular fiscal year is greater than the cash-out, resulting in some amount of unused cash. The unused cash is assumed to be rolled over to the following fiscal year in the current model. As a result, the cash-in for the following fiscal year is modified when all eligible activities within a particular fiscal year are scheduled with some unused cash. At the conclusion of a fiscal year t, the agency's cash-out is represented by R_t in Eq. (5) and the agency's cash-in is represented by G_t in Eq. (6).

$$R_t = \sum_{q=1}^{t} O_q \tag{5}$$

$$G_t = \sum_{q=1}^{t} I_q \tag{6}$$

2.2 Objective Function

In principle, extensions in the completion of the individual projects within portfolios are anticipated as a result of scheduling multiple projects simultaneously under constrained budgets. These anticipated extensions are inversely proportional to the available budget. Therefore, anticipated extensions in the completion of individual projects are considered as being the conflicting objectives. The multi-objective optimization algorithms minimize the anticipated extensions in the completion of the individual projects.

The minimization of the anticipated extensions in completion of each individual project D_j is achieved by the multi-objective optimization model. Accordingly, the number of the objectives in the problem matches the number of projects in the portfolio. The formulation of the objective function is given in Eqs. (7) and (8).

$$Minimize: \quad D_j\,(x_j),\ j = j_1,\ldots, j_m \tag{7}$$

$$x_j = (s_{1,j},\ \ldots, s_{i,j},\ \ldots\ , s_{n,j}) \tag{8}$$

Where; D_j represents the extension in the completion of project *j*; m is the number of projects in portfolio; x_j is a vector that represents the start times of the activities of a candidate schedule, including the project's start activity which establishes the project's start time; $s_{i,j}$ represents the start time of activity a_i in project *j*; and n represents the number of activities in project *j*.

2.3 Model Constraints

The optimization model takes into account the satisfaction of the constraints that describe the dependencies between activities and the limited fund available for each fiscal year. This means that, if activity's a_i predecessors are kept in a set P_i, the start time s_i of activity a_i in Eq. (9) is higher than or equal to the finish times f_{a_k} of all its predecessors a_k in P_i. Additionally, the portfolio's R_t as of the conclusion of fiscal year t should be greater than G_t as in Eq. (10).

$$s_i \geq f_{a_k} \quad \forall a_k \in P_i \tag{9}$$

$$R_t \leq G_t \quad \forall\, t \tag{10}$$

2.4 Multi-objective Algorithms

This section presents the three employed multi-objective optimization algorithms in this study. The Strength Pareto Evolutionary Algorithm (SPEA-II) and the Non-dominated Sorting Genetic Algorithm (NSGA-II) are two examples of Multi-Objective Evolutionary Algorithms (MOEA), while the Multi-Objective Particle Swarm Optimization algorithm (MOPSO) is a swarm algorithm.

2.4.1 SPEA-II

SPEA-II was first proposed by Zitzler *et al.*, [42] as an improved algorithm of SPEA [43]. SPEA-II has been recognized as an efficient algorithm to solve different types of multi-objective problems (MOP) [44,45]. In SPEA-II, a fine-grained fitness assignment strategy is implemented where the fitness of each individual depends on the number of individuals that it dominates and that are dominated by it. Also, a fixed-size external repository is used to keep the best solutions. If the number of non-dominated solutions is smaller than the capacity of the repository, the best dominated solutions may be added to fill up. However, having non-dominated solutions more than the capacity of the repository, a special archive truncation method is adopted in which boundary solutions are preserved.

2.4.2 NSGA-II

NSGA-II, which was firstly proposed by Deb *et al.,* [46], has been one of the most prominent algorithms to solve various MOP. In a survey conducted on the use of multi-objective algorithms in construction project management during the period 2012-2016, Alothaimeen and Arditi [47] reported that NSGA-II was the most commonly used algorithm. Recent applications of NSGA-II in project management included sustainability development, green construction, and carbon emissions as optimization objectives [48,49]. In NSGA-II, fitness is assigned according to a two-level criteria, the first depends on the dominance rank of the individuals, whereas the second is assigned considering the crowding distance of the individuals of the same dominance rank. In contrary to SPEA-II, no external repository is used in NSGA-II. However, the best individuals are preserved by keeping the best individuals from both the parents and the children after the generation of the children in each iteration.

2.4.3 MOPSO

The main algorithm was adopted from Ünal and Kayakutlu [50]. In the current study, a mutation operator of a random immigrant considering a decaying rate of 0.5 similar to that used in Ünal and Kayakutlu [50] was implemented. While the MOEA algorithms of SPEA-II, and NSGA-II adopt the crossover operator, the MOPSO involves algorithm-related operators to guide the flow of the swarm particles. Also, a repository of non-dominated individuals with a maximum capacity was maintained. However, the algorithm used in the current study differs from that presented in Ünal and Kayakutlu [50] in two aspects. Firstly, in the current study, when having more non-dominated individuals than the repository maximum capacity, individuals are eliminated considering the crowding distance. The crowding distance of non-dominated individuals was calculated similar to the one used in Deb *et al.*, [46]. Secondly, a procedure similar to the one used in Abido [51] was implemented in the current study to find the local and the global best guide for each particle. In the current study, the self-learning and the social learning factors were adopted as 0.5 and one, respectively.

2.5 Representation system

The random key (RK) indirect representation system, first put forth by Bean [52], was employed in the current research. The RK allows for the implementation of the classical operators while ensuring the schedules' feasibility. However, the utilization of RK requires the use of a special serial-schedule heuristic to obtain the schedules. Another problem of the RK is that different RK chromosomes in MOEA or particles in MOPSO may result in the same schedule. Schedules are indirectly defined using RK by giving each activity a relative scheduling priority. The length of the chromosomes in the MOEA and the particles in MOPSO is equal to the number of projects' activities. Every gene in a chromosome represents one activity and has an RK value between zero and one. This RK value represents the priority of the activity's scheduling in comparison to the other activities. Higher scheduling priority is indicated by a bigger RK value. The creation of the initial population in MOEA and swarm in MOPSO is done by randomly assigning the RK values.

2.6 Special serial-schedule heuristic

In the current study, a special serial-schedule heuristic is developed to obtain schedules from the RK chromosomes/particles. There are two stages involved in the heuristic. First, two sets of ordered and unordered activities are started, with the unordered set including all of the activities at first. Each step is carried out by first determining which activities are eligible, then choosing one activity, and finally transferring the chosen activity to the ordered set. The ordered activities are sequentially scheduled in the second stage, taking into account budgetary and precedence constraints. It should be noted that the implementation of the two stages of the heuristic is computationally expensive. Figure 2 shows the flow chart for the special serial-schedule heuristic.

3. Results and Discussions

Though the budget allocation in real portfolios is typically made based on long planning horizons of multiple fiscal years, the illustrative case portfolio adopts a shorter planning horizon of only six months to make the problem of manageable size. The case portfolio is composed of two projects *A* and *B*, which encompass four and six activities respectively. The contractual terms of projects *A* and B are presented in Table 1. The first row in Table 1 shows that projects *A* and *B* are initially scheduled to start on day zero, which marks the beginning of the six-month planning horizon. The relationships, duration, and prices of the activities are presented in Table 2. The activities' start times in the initial schedules of projects *A* and *B* are shown in the third column in Table 3. The durations of projects *A* and *B* span 42 and 51 working days respectively as indicated by the finish times of the terminating activities *DA* and *FB* of projects *A* and *B* respectively.

Table 4 presents the agency's monthly cash-out in the first row, which represents the collective payment schedule of the contractors of projects *A* and *B* during the six-month planning horizon, and the agency's monthly budget amounts, which represent the agency's monthly cash-in, in the second row. The last two rows in Table 4 present the cumulative agency's cash-out and cash-in, which have identical total amount of $261,000. The selection of projects A and B in the portfolio when the budget allocation process was performed was based on the fact that the total cost of projects *A* and *B*, which amounts to $261,000 was exactly matching the agency's budget available. However, the conducted cash flow analysis revealed that the cash-in amounts of $42,000 and $79,350 available during the second and third months are inadequate to cover the cash-out amounts of $91,600 and $136,800, respectively as presented in Table 4. The budget deficits during the second and third months are huge enough to create additional budget deficits during the fourth and fifth months as indicated by the cumulative cash-out and cash-in values in the last two rows in Table 4. Unless this cash flow problem is resolved, financial issues are anticipated which can potentially compromise the success of the projects. To balance the agency's cash-out and cash-in on a monthly basis, activities of the two projects need to be simultaneously rescheduled to achieve the sought balance while minimizing possible extensions in the completion of projects *A* and *B*.

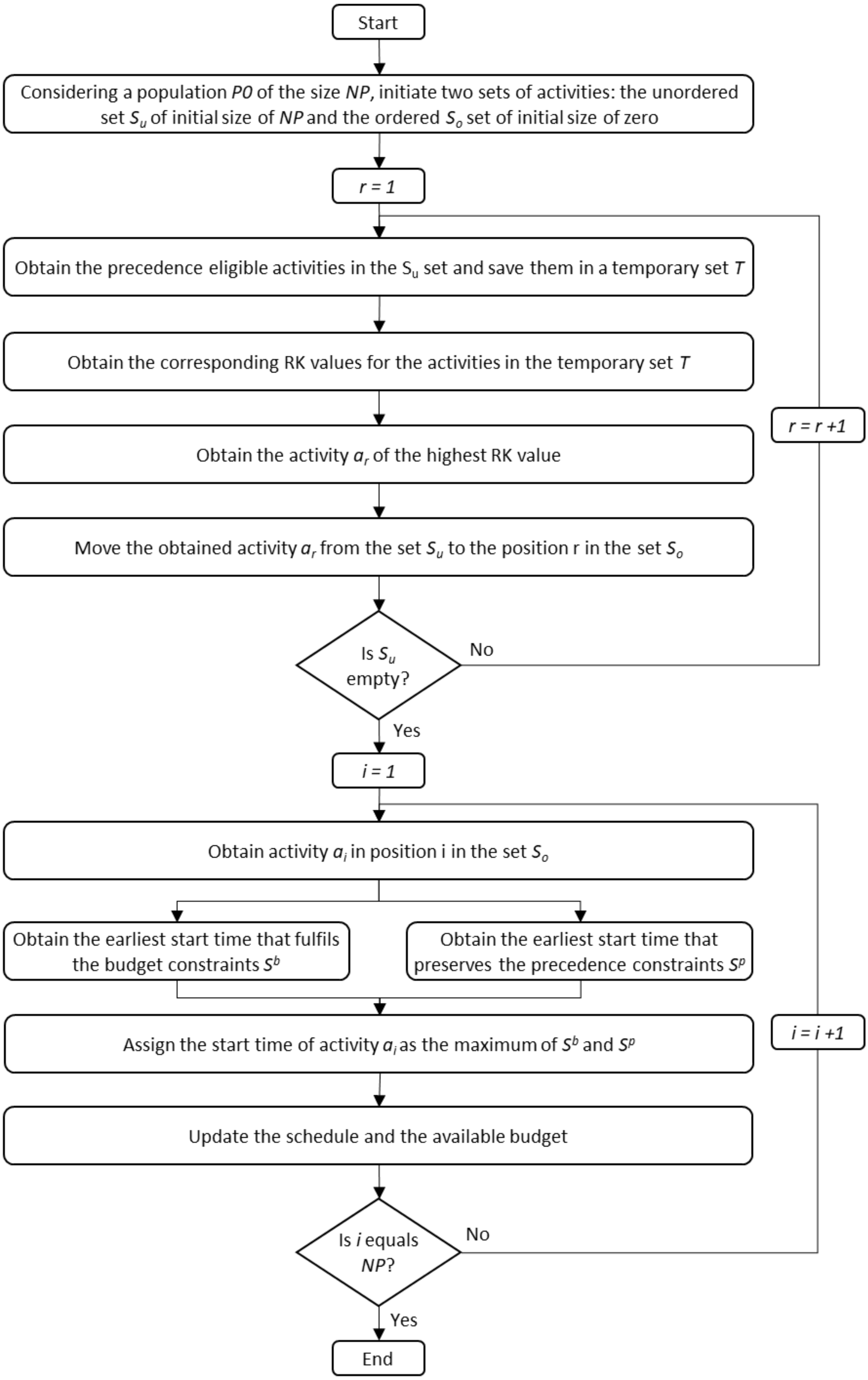

Fig. 2. Special serial-schedule heuristic

Table 1
Contractual terms of projects *A* and *B*

Contract terms	Project *A*	Project *B*
Original commencement (day #)	0	0
Advance payment (%)	5	5
Lag of paying advance payment from project's commencement (day)	0	0
Retained (%) of interim pay requests	5	10
Lag of paying retained money from project's completion (month)	1	1
Billing period duration (month)	1	1
Lag of paying received bills (month)	1	1

Table 2
Activities relationship, duration, and prices of projects *A* and *B*

Project	Activity ID	Predecessor	Duration (day)	Prices ($)
A	AA	-	17	17000
	BA	AA	15	30000
	CA	AA	12	48000
	DA	BA, CA	10	30000
B	AB	-	15	30000
	BB	AB	10	20000
	CB	AB	15	30000
	DB	BB	12	24000
	EB	CB	11	22000
	FB	DB, EB	10	10000

Table 3
Original start times and the start times of the best compromise solutions of projects *A* and *B*

Project	Activity	Start times			
		Original	SPEA-II	NSGA-II	MOPSO
A	AA	0	0	1	1
	BA	17	18	45	18
	CA	17	17	34	18
	DA	32	41	65	33
B	AB	0	1	0	0
	BB	15	22	20	57
	CB	15	44	15	15
	DB	25	32	33	67
	EB	30	59	30	65
	FB	41	70	45	79

Table 4
Cash-out and cash-in of the original solution of projects *A* and *B*

Parameters	One-month fiscal periods					
	1	2	3	4	5	6
Cash-out ($)	13,050	91,600	136,800	19,550	-	-
Cash-in ($)	13,050	42,000	79,350	63,540	48,000	15,060
Cumulative Cash-out ($)	13,050	104,650	241,450	261,000	261,000	261,000
Cumulative cash-in ($)	13,050	55,050	134,400	197,940	245,940	261,000

The case portfolio was solved using the three multi-objective algorithms. The population/swarm sizes of five were selected for the three algorithms while the sizes of the external repository for SPEA-II and MOPSO were set as five. The five obtained Pareto solutions of the three algorithms are presented in Table 5 using the parameters presented in the bottom of Table 5. The Pareto front of each algorithm involves five non-dominated solutions. The three algorithms obtained the same boundary solutions, i.e., solutions of minimum extensions in completion of projects *A* and *B*. The first solution, that achieves the global minimum extension of project *A* to zero, should be selected if the decision maker's preference is to minimize the extension of project *A*. While the first solution minimizes the extension in project *B* to 44 days, this is not the global minimum extension of project *B*. The 44-day extension in project *B* is definitely higher than its globally minimum extension of zero associated with the fifth solution. On the other hand, the fifth solution globally minimizes the extension of project *B* to zero, and minimizes, but not globally minimizes, the extension of project *A* to 48 days.

Table 5
Extensions of Pareto solutions of projects *A* and *B*

Pareto solutions	Extensions in completion of projects (days)							
	SPEA-II[a]		NSGA-II[a]		MOPSO[b]		Elite Pareto set	
	A	*B*	*A*	*B*	*A*	*B*	*A*	*B*
1	0	44	0	44	0	44	0	44
2	1	37	1	37	1[c]	38[c]	1	37
3	9[c]	29[c]	13	29	13	29	9	29
4	33	7	33[c]	4[c]	33	9	33	4
5	48	0	48	0	48	0	48	0

[a] 100 iterations, single-point crossover, 80% crossover probability, new-chromosome mutation, 15% mutation rate.
[b] 100 iterations, 0.4 initial weight, 0.5 self-learning factor, 1.0 social-learning factor, new-particle mutation, 0.5 mutation probability/decaying rate.
[c] Best compromise solutions.

Table 5 presents the trade-off between the minimum extensions of projects *A* and *B*, which is represented by the three additional solutions that each algorithm offers in addition to the boundary solutions. Although the extensions in projects *A* and *B* are minimized in each of these three methods, they are not globally minimized. Since each of these five solutions consists of two optimized values for each of the two objectives, they are all considered to be the best possible solutions. That is, concerning the values of the two objectives, no solution is superior than any other. To strike a balance between the extensions of the two projects, the best compromise solution, as found by Dhillon *et al.,* [53] can be used when there is no reason to favor a specific project. As presented in Table 5, different best compromise solutions were attained using the three algorithms.

To illustrate the RK representation, and the special serial-schedule heuristic, which balances the agency's cash-out with cash-in, one of the obtained solutions is explained in detail. Figure 3 shows chromosome *a*, which characterizes the best compromise solution of SPEA-II in Table 5. As explained above, the special serial-schedule heuristic involves two stages; (1) define the scheduling order of the activities based on the RK values, (2) determine the activities' earliest start time that fulfills both the precedence and the budget constraints. Figure 4 shows the output of the first stage of the heuristic which defines the scheduling order of all projects' activities according to the heuristic flow chart shown in Figure 2. In the second stage, the start times are determined for the best compromise solutions of the three algorithms, which are presented in Table 3. The fourth column in Table 3 presents chromosome *a* of the best compromise solution of SPEA-II which indicates the activities' start times that fulfill the precedence and budget constraints. Table 6 presents the original schedules of payments for the contractors of projects *A* and *B* and the optimized schedules of payments that correspond to chromosome *a*. The detailed calculations of the amounts of bills in Table 6 are presented in Table 7. Figure 5 shows the rescheduled activities of projects *A* and *B* of chromosome *a* and the start and finish dates of the billing periods. It should be noted that Figure 5 depicts one-day delay in project *B*'s planned start date.

AA	BA	CA	DA	AB	BB	CB	DB	EB	FB
0.47	0.39	0.47	0.68	0.40	0.37	0.29	0.40	0.99	0.13

Fig. 3. Chromosome *a* of the best compromise solution of SPEA-II

AA	CA	AB	BA	DA	BB	DB	CB	EB	FB

Fig. 4. Scheduling order of activities according to chromosome *a*.

Table 6
Schedules of payments according to the original schedule and chromosome *a*

Solution	Project	Parameter	One-month fiscal periods					
			1	2	3	4	5	6
Original	A	Bill ($)	47,000	78,000	-	-	-	-
		Payment ($)	6,250	42,300	76,450	-	-	-
	B	Bill ($)	58,000	71,000	7,000	-	-	-
		Payment ($)	6,800	49,350	60,350	19,550	-	-
	A&B	Payment ($)	13,050	91,600	136,800	19,550	-	-
Chromosome *a*	A	Bill ($)	45,000	59,000	21,000	-	-	-
		Payment ($)	6,250	40,500	53,100	25,150	-	-
	B	Bill ($)	-	32,000	44,000	40,000	20,000	17,000
		Payment ($)	6,800	-	27,200	37,400	47,600	-
	A&B	Payment ($)	13,050	40,500	80,300	62,550	47,600	17,000

Table 7
Detailed calculations of the bills and payments of chromosome *a*

Project	Bill	Activity	Performed duration (days)	Daily price ($)	Bill amount ($)	Payment amount ($)	Bill period	Payment period
A	A1	AA	17	1000	45,000	40,500	1	2
		AB	4	2000				
		AC	5	4000				
	A2	BA	11	2000	59,000	53,100	2	3
		CA	7	4000				
		DA	3	3000				
	A3	DA	7	3000	21,000	19,800	3	4
B	B1	AB	15	2000	32,000	27,200	2	3
		BB	1	2000				
	B2	BB	9	2000	44,000	37,400	3	4
		CB	1	2000				
		DB	12	2000				
	B3	CB	14	2000	40,000	34,000	4	5
		EB	6	2000				
	B4	EB	5	2000	20,000	17,000	5	6
		FB	10	1000				

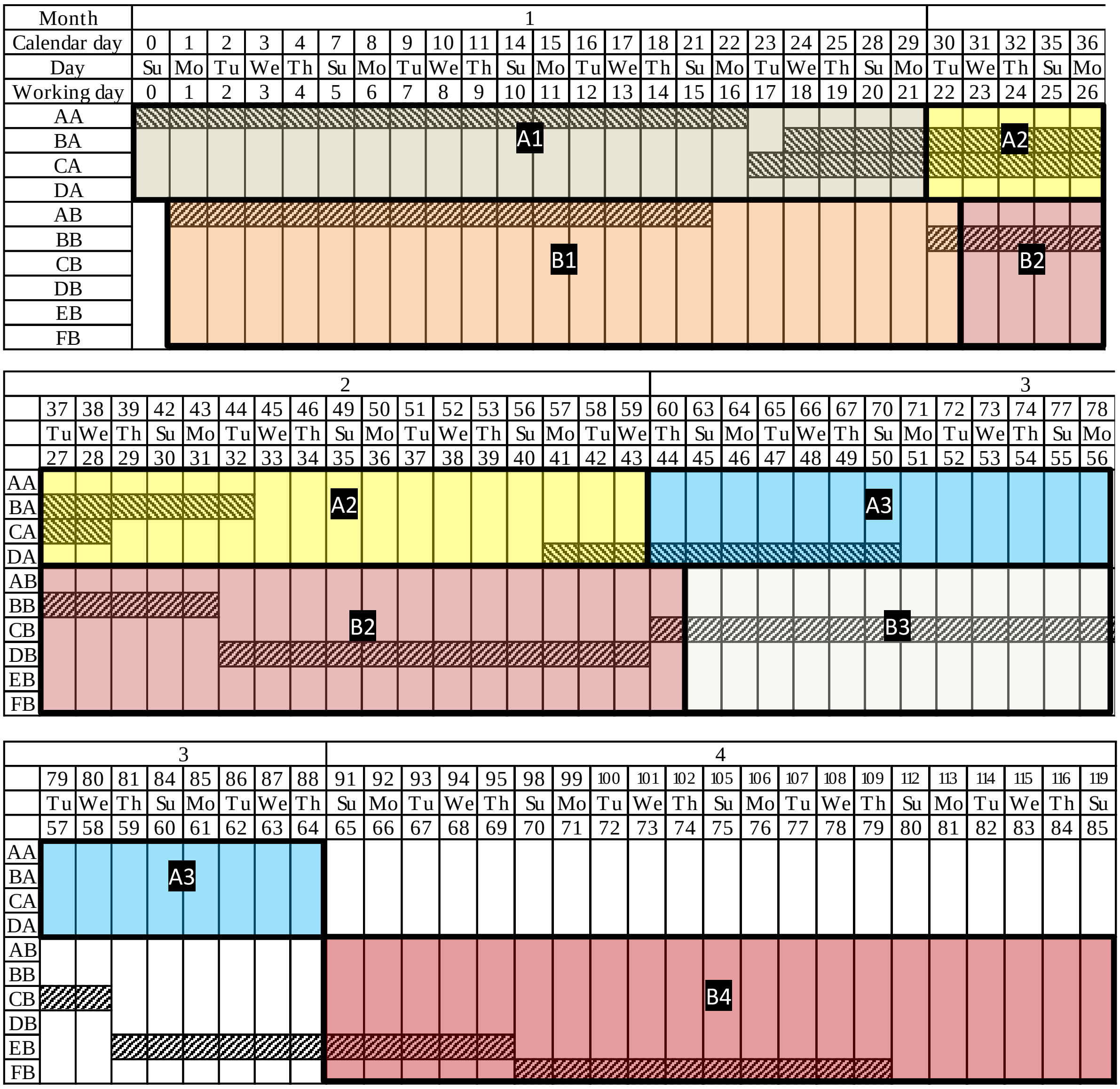

Fig. 5. Bar chart of the chromosome *a* presenting the activities and billing periods of projects *A* and *B*

The cash-out of chromosome *a* and the best compromise solutions of the three algorithms during the fiscal monthly periods are presented in Table 8. It ought to be noted that the cumulative cash-out values of the three algorithms in Table 8 are balanced with the cumulative cash-in values in the last row in Table 4 during the six fiscal periods.

Table 8
Cash-out of the best compromise solutions of SPEA-II, NSGA-II, and MOPSO

Algorithm	Cash-out ($)	One-month fiscal periods					
		1	2	3	4	5	6
SPEA-II	Period	13,050	40,500	80,300	62,550	47,600	17,000
	Cumulative	13,050	53,550	133,850	196,400	244,000	261,000
NSGA-II	Period	13,050	40,800	79,900	63,400	36,850	27,000
	Cumulative	13,050	53,850	133,750	197,150	234,000	261,000
MOPSO	Period	13,050	37,400	62,150	83,800	48,450	16,150
	Cumulative	13,050	50,450	112,600	196,400	244,850	261,000

As presented in Table 9, some amounts of cash occasionally remain unutilized at the end of some fiscal months, which are rolled over to the following month. For instance, an unutilized cash amount of $1,500 during the second month was moved to the third month, which raised the cash-in from $79,350 to $80,850 as shown in Table 9. The updated cash-in values are presented in the second row in Table 9 for the six fiscal months. Now, it is obvious that the contractors' payment schedule of chromosome a, which is presented in the last row of Table 6, became affordable by the agency's budget, which is presented as the updated cash-in values in the second row in Table 9. Figure 6 shows the cumulative cash-in and the cumulative cash-out of the original projects' schedules. In addition, Figure 6 shows the optimized cash-out for the best compromise solutions of SPEA-II, NSGA-II, and MOPSO. Figure 6 demonstrates the capability of the algorithms to balance the owners' cash-out with the cash-in during the six-month planning horizon.

Table 9
Periodical cash-in and utilized cash of chromosome a

Parameter	One-month fiscal period					
	1	2	3	4	5	6
Cash-in ($)	13,050	42,000	79,350	63,540	48,000	15,060
Updated cash-in ($)	13,050	42,000	80,850	64,090	49,540	17,000
Cash-out ($)	13,050	40,500	80,300	62,550	47,600	17,000
Cumulative unutilized cash ($)	0	1,500	550	1,540	1,940	0

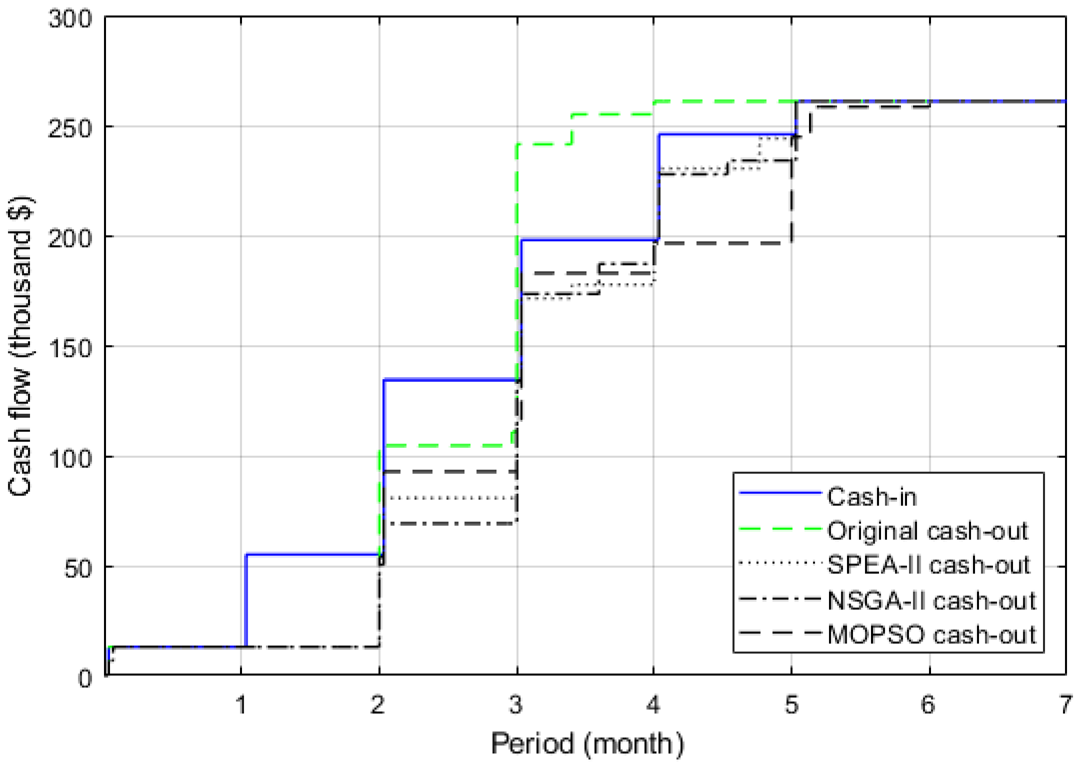

Fig. 6. Balanced cash-out with cash-in using SPEA-II, NSGA-II, and MOPSO

4. Benchmarking

To evaluate the quality of the Pareto fronts obtained by the individual algorithms, the Pareto solutions of the three algorithms were combined and the elite Pareto front was obtained by applying the dominance conditions. The elite set of the Pareto solutions is presented in the last column in

Table 5. Then, the contributions of the individual algorithms to the elite Pareto front were determined. The higher the contribution of a particular algorithm to the elite Pareto front the better quality of the algorithm's Pareto solutions. The results in the last column in Table 5 are such that only two of the MOPSO Pareto solutions belong to the elite Pareto front whereas four of the SPEA-II and NSGA-II solutions belong to the elite Pareto front. This finding clearly indicates that SPEA-II and NSGA-II contributed to the elite Pareto front more significantly compared to MOPSO.

In addition, the measure of "set coverage" was used, which was firstly introduced by Zitzler and Thiele [43]. This measure is used to evaluate the quality of the obtained Pareto fronts by calculating the percentage of Pareto solutions of each algorithm that is covered by the Pareto solutions of other algorithms. Generally, high coverage percentages reflect better quality of Pareto solutions. The set coverage percentages were calculated and presented in Table 10, which indicate that SPEA-II exhibited the best performance by covering 80% and 100% of the Pareto solutions of NSGA-II and MOPSO, respectively. The NSGA-II exhibited comparable performance by covering 80% and 100% of the Pareto solutions of SPEA-II and MOPSO, respectively. MOPSO was found to have the worst performance by covering only 40% and 60% of the Pareto solutions of SPEA-II and NSGA-II, respectively.

Table 10
Values of the set coverage measure

Set A	SPEA-II		NSGA-II		MOPSO	
Set B	NSGA-II	MOPSO	SPEA-II	MOPSO	SPEA-II	NSGA-II
Case program	80.0	100.0	80.0	100.0	40.0	60.0

Further, the quality of the obtained Pareto fronts was evaluated using the performance metrics of computational time, diversity Δ, spacing *SP*, and hypervolume *HV* where the values are presented in Table 11. The performance metric (Δ) was introduced by Deb *et al.,* [46] to measure the extent of the spread of the non-dominated solutions, as well as the uniformity of their distribution. The spacing metric (*SP*), which was first proposed by Schott [54] is a diversity metric that is used to assess the spreading uniformity of the solutions in the obtained Pareto front. Another metric is the hypervolume (*HV*) which evaluates both the convergence and the diversity of the obtained Pareto solutions [55]. Considering the computational time, the SPEA-II Pareto front was obtained in 0.97 seconds compared to 1.02 and 1.28 seconds of NSGA-II and MOPSO, respectively. Regarding diversity, the results are such that the three algorithms have identical values of the diversity metric Δ, which indicate similar spreading of the Pareto solutions of the three algorithms. However, a better spacing metric *SP* value was achieved by MOPSO indicating a higher uniformity of MOPSO Pareto solutions. With respect to the hypervolume *HV* metric, SPEA-II and NSGA-II exhibited the same value of 0.77 compared to 0.76 of MOPSO. This indicates that the obtained Pareto fronts of SPEA-II and NSGA-II have a comparable performance regarding convergence/diversity.

Table 11
Values of the performance metrics

Parameter	Algorithm		
	SPEA-II	NSGA-II	MOPSO
Computational time (s)	0.97	1.02	1.28
Diversity metric	0.96	0.96	0.96
Spacing metric	9.66	9.12	7.91
Hypervolume metric	0.77	0.77	0.76

The three algorithms of SPEA-II, NSGA-II, and MOPSO were benchmarked using five case portfolios of CP-1, CP-2, CP-3, CP-4, and CP-5 each portfolio comprises two large-size projects. The project networks of the five case portfolios were developed using MPSPLib. The projects of the case portfolios include 20, 30, 90, 120, and 240 activities. Table 12 presents the sizes of the population/swarm as well as the external repository set. The same parameters presented in the bottom of Table 5 were used to solve the five case portfolios. The experiments were implemented on a laptop with Intel(R) Core (TM) i7-4500U CPU@1.80 GHz 2.40 GHz processor and 8 GBs RAM. The algorithms were coded using MATLAB 2018a.

Table 12
Sizes of the population/swarm and external set/archive for the five case portfolios

Case portfolio	Projects' activities	Size of population/swarm			Size of the external set/archive	
		SPEA-II	NSGA-II	MOPSO	SPEA-II	MOPSO
CP-1	20	15	15	15	15	15
CP-2	30	20	20	20	20	20
CP-3	90	40	40	40	40	40
CP-4	120	60	60	60	60	60
CP-5	240	100	100	100	100	100

The obtained results proved the capability of the algorithms to obtain Pareto fronts of feasible solutions. However, due to the nature of the current scheduling problem, solutions of different activities' start times but of identical extension value were encountered in the obtained Pareto fronts. Table 13 presents the number of unique solutions of RK chromosomes/particles, schedules, and extension values. For all case portfolios, NSGA-II was able to obtain the largest number of solutions of unique schedules. In three out of the five case portfolios, NSGA-II obtained identical or bigger number of solutions of unique extension values compared to the other algorithms. These results indicate that, comparing NSGA-II to SPEA-II and MOPSO, the latter two algorithms have less capability of exploring the search space.

Table 13
Number of unique solutions in the obtained Pareto fronts of the five case portfolios

Case portfolio	SPEA-II			NSGA-II			MOPSO		
	RK	Schedule	Extension	RK	Schedule	Extension	RK	Schedule	Extension
CP-1	15	15	15	15	15	13	15	15	15
CP-2	16	12	9	20	20	11	20	12	8
CP-3	26	15	15	40	40	16	40	26	16
CP-4	36	19	12	56	56	18	60	21	15
CP-5	75	47	29	100	100	36	100	80	39

Evaluating the quality of the obtained Pareto fronts involves comparing the boundary solutions based on the extensions presented in Table 14. To compare the boundary solutions obtained by the algorithms, the summation of the distance between the boundary solutions of minimum extension in project *A* in the algorithm's Pareto front and the elite Pareto front, and the distance between the boundary solutions of minimum extension in project *B* in the algorithm's Pareto front and the elite Pareto front was calculated. As presented in Table 15, NSGA-II was able to obtain better boundary solutions, which exhibit less distance values, compared to SPEA-II and MOPSO in four out of the five case portfolios.

Table 14
Extensions of projects *A* and *B* for the boundary and best compromise solutions of the five case portfolios

Algorithm	Solution	Extensions (days)									
		CP-1		CP-2		CP-3		CP-4		CP-5	
		A	*B*	*A*	*B*	*A*	*B*	*A*	*B*	*A*	*B*
SPEA-II	Boundary solution I	0	202	0	131	0	134	0	160	130	706
	Best compromise solution	0	202	136	27	0	134	23	127	153	618
	Boundary solution II	180	0	138	26	151	0	184	0	706	0
NSGA-II	Boundary solution I	0	197	0	130	0	109	0	163	130	706
	Best compromise solution	0	197	0	130	0	109	27	129	155	618
	Boundary solution II	180	0	172	0	157	0	189	0	703	0
MOPSO	Boundary solution I	0	194	0	112	0	118	0	148	130	706
	Best compromise solution	0	194	0	112	0	118	151	33	155	618
	Boundary solution II	185	52	159	33	182	0	208	0	704	0

Table 15
Distance between the boundary solutions of the algorithm's Pareto front and the boundary solutions of the elite Pareto front

Case portfolio	Distance		
	SPEA-II	NSGA-II	MOPSO
CP-1	8.0	3.0	52.2
CP-2	61.8	18.0	35.5
CP-3	25.0	6.0	40.0
CP-4	12.0	20.0	24.0
CP-5	3.0	0.0	1.0

Further, NSGA-II was found to contribute the most to the set of the elite Pareto solutions in the five case portfolios as presented in Table 16. On average, solutions from NSGA-II constitute 52.1% of the solutions of the elite Pareto, compared to averages of 27.7% and 20.2% for SPEA-II and MOPSO, respectively. Moreover, Table 17 presents the percentage of Pareto solutions of each algorithm that is covered by the Pareto fronts of other algorithms. Pareto solutions of NSGA-II were found to cover 40.0% to 63.8% with an average of 49.5% of the Pareto solutions of SPEA-II, and 41.7% to 96.2% with an average of 67.4% of the Pareto solutions of MOPSO. The Pareto solutions of SPEA-II were found to cover between 10% to 76% with an average of 48.4% of the Pareto solutions of NSGA-II, and 41.7% to 81.3% with an average of 58.8% of the Pareto solutions of MOPSO. The Pareto solutions of MOPSO were found to cover between 20.0% to 51.1% with an average of 33.4% of the Pareto solutions of SPEA-II, and 2.5% to 40.0% with an average of 24.9% of the Pareto solutions of NSGA-II. Thus, NSGA-II performance was the best while MOPSO exhibited the worst performance.

The measured values of the performance metrics of the three algorithms for the five case portfolios are presented in Table 18. With respect to the computational time, MOPSO takes substantially more time compared to SPEA-II and NSGA-II. This can largely be attributed to the implementation of a time-consuming strategy to select the local and global best guide for the particles [51]. Regarding the diversity metric Δ, NSGA-II scored lower values compared to SPEA-II and MOPSO in case portfolios CP-2, CP-3, and CP-4 which indicates Pareto fronts of better spread and distribution. With respect to the spacing metric *SP*, NSGA-II and MOPSO were better compared to

SPEA-II. Each of the NSGA-II and MOPSO were found to have the lowest *SP* value in two case portfolios. Thus, the distribution uniformity of the solutions of the obtained Pareto fronts was generally better in NSGA-II and MOPSO compared to SPEA-II. With respect to the hyper-volume metric *HV* values, the obtained Pareto fronts of SPEA-II and NSGA-II exhibited slightly higher *HV* values, compared to the MOPSO. This indicates better convergence/diversity for SPEA-II and NSGA-II compared to MOPSO. Consequently, Pareto fronts of better spread, distribution, and convergence are more likely to be obtained using NSGA-II compared to SPEA-II and MOPSO. Generally, MOPSO Pareto fronts are of the worst spread, diversity, and convergence. In addition, MOPSO was found to consume a substantially higher computational time to solve the optimization problem.

Table 16
Percent contributions to the elite Pareto front

Case portfolio	Contributions (%)		
	SPEA-II	NSGA-II	MOPSO
CP-1	27.3	50.0	22.7
CP-2	21.7	47.8	30.4
CP-3	42.9	57.1	0.0
CP-4	24.3	51.4	24.3
CP-5	22.2	54.2	23.5
Average	27.7	52.1	20.2

Table 17
Percentages of non-dominated solutions of set B algorithms covered by those in set A algorithms

Set A	SPEA-II		NSGA-II		MOPSO	
Set B	NSGA-II	MOPSO	SPEA-II	MOPSO	SPEA-II	NSGA-II
CP-1	20.0	53.3	60.0	66.7	33.3	26.7
CP-2	10.0	41.7	41.7	41.7	41.7	40.0
CP-3	70.0	65.4	40.0	96.2	20.0	2.5
CP-4	66.1	52.4	42.1	52.4	21.1	32.1
CP-5	76.0	81.3	63.8	80.0	51.1	23.0
Average	48.4	58.8	49.5	67.4	33.4	24.9

5. Practical implications

While the budget allocation ensures that funds are available during the planning horizon of multiple fiscal years to support the selected maintenance projects, cash needs to make contractors' payments during some fiscal years might exceed the allocated budgets during these fiscal years. Furthermore, variations in the budgets anticipated for the portfolio and modifications in the projects occasionally occur, which potentially result in negative cash flow problems that definitely affect the progress of the projects. In addition, changes in business environment mandates agencies to continually re-assess the priority of projects to conform with the strategic goals of the portfolios. Therefore, the cash flow management functions of forecasting, planning, monitoring, and controlling of cash flow is very crucial for the achievement of the goals of the programs.

The merits of the scheduling model include: (1) determine the exact due dates and amounts of the contractors' payments; (2) establish feasible schedules to help owners fully utilize their budgets. In addition, the model allows to continually optimize the updated schedules resulting from the project monitoring and control process. Furthermore, the information on new projects often change in response to factors including the variations in the funding anticipated and the projects' modifications required. The changes in these factors and others require a re-assessment of the priority list of projects to conform with the strategic goals of the agency's portfolio. The proposed scheduling model can be continually used during the execution phase to handle these factors through changing projects' priorities and optimizing schedules.

Table 18
Performance metrics values of SPEAII, NSGA-II, and MOPSO

Case portfolio	Performance metric	Value		
		SPEA-II	NSGA-II	MOPSO
CP-1	Computational time (s)	9.77	11.71	19.06
	Diversity metric	0.88	0.97	0.88
	Spacing metric	17.72	26.43	15.29
	Hypervolume metric	0.72	0.73	0.72
CP-2	Computational time (s)	24.71	23.23	35.35
	Diversity metric	1.05	1.04	1.06
	Spacing metric	14.70	17.80	18.52
	Hypervolume metric	0.74	0.73	0.73
CP-3	Computational time (s)	370.32	402.03	473.74
	Diversity metric	1.09	1.06	1.08
	Spacing metric	12.27	10.24	10.79
	Hypervolume metric	0.73	0.74	0.70
CP-4	Computational time (s)	878.86	1031.01	1033.82
	Diversity metric	1.20	1.12	1.16
	Spacing metric	13.98	10.20	11.20
	Hypervolume metric	0.74	0.73	0.71
CP-5	Computational time (s)	6734.41	7051.54	8907.98
	Diversity metric	1.43	1.38	1.33
	Spacing metric	31.92	33.34	31.00
	Hypervolume metric	0.74	0.74	0.73

6. Conclusions

This study addresses a significant gap in research and practice representing the fact that highway and bridge agencies make budget allocations for M&R projects during the planning stage at the network-level while ignoring the closely-related aspect of cash flow. This shortcoming can potentially result in cash flow problems during the construction stage, which can delay the progress and compromise the successful completion of the projects. Since most M&R projects are outsourced, agencies must carefully plan their cash flow. Situations may arise wherein the agency's budget for some fiscal years cannot meet the contractors' payment schedules if cash flow is not properly planned.

This research reintroduces the FBS from the perspective of portfolio owners. A FBS model is developed to schedule the activities of the portfolio projects, utilize the schedules to define the payment schedules of projects' contractors, calculate the agencies' cash needs during the fiscal years, and utilize the multi-objective optimization algorithms of NSGA-II, SPEA-II, and MOPSO to optimize the projects' schedules to achieve a balance between the cash needs during the fiscal years and the available budgets. The output presents to the decision maker a Pareto front with a set of solutions, each solution involves the optimized schedules of the individual projects. Thus, the Pareto fronts facilitate decision-making regarding the selection of the most appropriate solution based on the set priority of projects for early completion.

Though the three multi-objective optimization algorithms of NSGA-II, SPEA-II and MOPSO successfully balanced agencies' cash-out with cash-in, they were benchmarked using case portfolios of different sizes. Generally, NSGA-II was found to outperform SPEA-II and MOPSO. In most of the case portfolios, NSGA-II obtained larger Pareto fronts of better convergence and broader spread compared to SPEA-II and MOPSO. Generally, MOPSO showed the least favorable performance in solving the current problem.

There are some features in the current study, which can be implemented differently in future research. First, the unused amount of the budget in a given fiscal year was rolled over to the following fiscal year. Some agencies might not allow to roll the unused budget over to the following fiscal year. Second, minimizing the multiple objectives representing the extensions in projects' completion was adopted in the current optimization model. Future research with contextual agencies' applications might consider minimizing the user cost or maximizing the effectiveness of M&R treatments.

Author Contributions

Conceptualization, A.E.; methodology, A.E. and A.F.; software, A.F.; validation, A.E. and A.F.; formal analysis, A.E. and A.F.; investigation, A.E. and A.F.; resources, A.F.; data curation, A.F.; writing—original draft preparation, A.E.; writing— A.E. and A.F.; visualization, A.F.; supervision, A.E., M.A.A.; project administration, A.E., M.A.A.; funding acquisition. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Any data supporting the reported results will be provided by the authors upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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