



# Balancing the portfolio of urban and public projects with distance-dependent coverage facilities

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Received 14 December 2018; received in revised form 25 August 2019; accepted 14 October 2019

## KEYWORDS

Project portfolio balancing;  
 Project selection;  
 Genetic algorithms;  
 Set covering;  
 Goal programming.

**Abstract.** The portfolio of urban and public projects should be balanced in terms of completion time, districts, and strategic objectives. For this purpose, we suggest a mixed-integer nonlinear programming model based on the goal programming approach. Projects are selected to minimize the squared deviation of urban and regional development indicators from their respective targets. In the proposed model there are two types of indicators: coverage indicators that are measured based on the distance of each neighborhood from the nearest covering facility, and general indicators that are usually measured based on the capacities and capabilities of each district. It is assumed that the location of covering facilities has already been selected, but the construction of these facilities will be prioritized and planned based on budget constraints and competition with other regional development projects. Numerical results show that the proposed genetic algorithm has superior performance compared with the Generalized Algebraic Modeling System (GAMS) solvers. Finally, the application of the model is illustrated by an example.

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## 1. Introduction

Project portfolio management involves two process groups: evaluation and selection of the right projects, and the correct implementation of these projects. In the first process group, the projects are evaluated, selected, and planned to maximize the realization of strategic objectives. The resulting portfolio must be balanced in terms of factors such as timing; coverage of all strategic objectives; impact across the business; current life cycle stage of projects; overall risk; and available resources [1]. Priority of these factors could vary in different organizations.

Project selection in urban and public sector management is a serious challenge, due to limited

resources and increasing social and economic pressures [2]. Decision-makers must deal with conflicting objectives and find an ideal mix of projects within the constraints of resources. This paper focuses on selecting and planning a balanced project portfolio of urban and public projects.

Bubble charts are among the tools suggested for checking and depicting the balance of a project portfolio [3]. Figure 1 shows a sample bubble chart. Each bubble represents a project. In urban management, rows and columns of bubble charts can be considered districts, and organizational objectives, respectively. When there are dozens or hundreds of projects, the bubble chart cannot be a good tool for checking the project portfolio balance. This paper presents a mathematical model for selecting a balanced portfolio of urban and public projects. Given that urban management is public and non-profit, the model aims not to make more profits, but to realize the objectives of urban development.

The fundamental theory of portfolio selection

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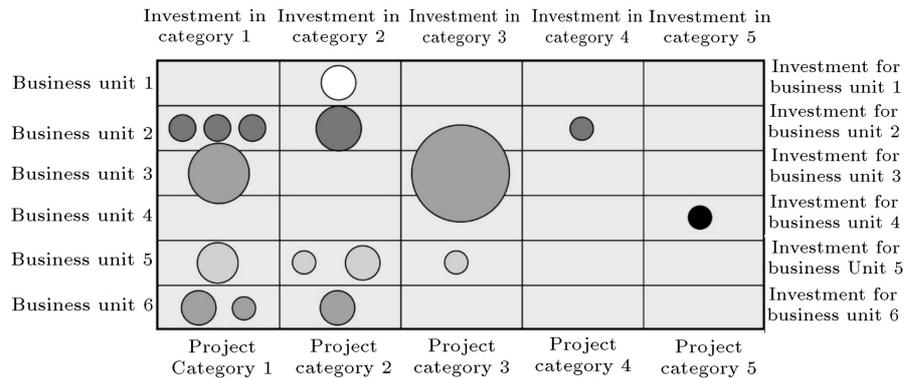


Figure 1. Bubble chart [3]

was first proposed by Markowitz [4]. The proposed portfolio selection problem is based on a single-period investment model. The researchers tried to develop the Markowitz model in different ways. To solve the project selection problem, the methods used are mainly categorized into two groups. The first group includes methods based on qualitative criteria, methods based on the opinions of a group of experts, and more on social issues. The second group consists of decision-making methods based on operational research which can be divided into two subgroups: multi-objective models and Multi-Attribute Decision-Making (MADM) models. For instance, Alvarez-García and Fernández-Castro [5], Kalashnikov et al. [6], and Khalili-Damghani et al. [7] used multi-objective decision-making methods, and Rafiee and Rabbani [8] and Jafarzadeh et al. [9] used MADM methods for solving the project selection problem. One of the disadvantages of using MADM for project selection is the lack of consideration of the interaction between projects.

Goal programming as an appropriate tool for decision-making in multi-objective situations attempts to bring each objective as close as possible to its goal. The first model of goal programming in the project portfolio selection was presented by Sharma et al. [10]. Bravo et al. [11] developed a goal programming model for selecting a project portfolio with multiple criteria. Ghahtarani and Najafi [12] presented a robust optimization model for selecting the project portfolio using the goal programming technique. Kocadağlı and Keskin [13] presented a fuzzy goal programming method to model the project selection problem. Tabrizi et al. [14] proposed a utility-based multi-choice goal programming technique that is applied to determine the project portfolio regarding the chosen criteria and some other operational limitations.

The literature review shows that relatively a few studies have been conducted to study the selection of a portfolio of urban and public projects. Huang et al. [15] applied the fuzzy analytical hierarchy process

method to select a portfolio of governmental projects. Litvinchev et al. [16] developed a multi-objective linear programming model for selecting a portfolio of urban R&D projects. Fernandez et al. [2] considered public project portfolio selection. They assume that there are a finite set of independent criteria describing social concerns. Each project produces certain effects on one or more of these criteria. They considered this problem to be a multi-objective optimization problem and proposed a non- outranked sorting genetic algorithm. Some of the key assumptions of their model: the effects of implemented projects realize at the end of the planning horizon; the social object under consideration is not disaggregated into geographical areas; there is no target for criteria and the objective is to maximize the new state of criteria. Arratia et al. [17] developed a mathematical model to select a portfolio of R&D projects of government agencies to realize public objectives. The projects are composed of tasks, cooperation at the level of the tasks is allowed, and the general and partial budget policy has been applied. Pujadas et al. [18] presented a MADM approach for evaluating, prioritizing, and selecting public investment projects. They used value function and hierarchical analysis methods. Roman [19] introduced a bi-objective optimization model for the selection and design of highway safety and travel time improvement projects with constraints on project costs and the types of improvement combinations admissible at project sites. Each objective function is a min-max model in which the decision-makers goal is to minimize the worst-case scenarios. A surrogate-assisted genetic algorithm is proposed as a heuristic solution for the presented bi-objective problem. Wu and Chen [20] provided a simple zero-one goal programming model for smart city project selection. The objective function is a linear summation of deviation from targets. Targets are defined for the whole city and there is no disaggregation of the city into districts or areas.

In a portfolio of urban and public projects, some project types should be selected considering demand

coverage. Fire stations, emergency services, and the police departments should have a high level of service to ensure public safety. Such centers should be built in areas with the highest coverage. These problems are instances of set covering problems. The integer programming model of set covering problem firstly was proposed by Toregas et al. [21] to locate emergency facilities. In this paper, it is assumed that the location of the required covering facilities has been previously selected and the establishment of each covering facility is defined as a project. Due to limited resources, projects related to any type of covering facility should compete with other projects. Therefore, in each period, some of the projects related to each type of covering facility may be implemented. To the best of our knowledge, none of the previous papers in the context of project portfolio selection consider the selection and planning of covering facilities.

Project selection in its simplest form is a knapsack problem that is NP-hard. When project selection is extended by adding features such as the timing of projects, or is considered as a multi-objective problem or is integrated with other problems such as project scheduling, its complexity increases; therefore, using metaheuristic approaches is a common practice. For example, Ghorbani and Rabbani [22] developed a multi-objective scatter search algorithm to solve the multi-objective project selection and timing problem. Yu et al. [23] developed a genetic algorithm to solve a non-linear project selection model. Wu et al [24] used a non-dominated sorting genetic algorithm to obtain the optimal portfolio of distributed energy generation projects. In this paper, we develop a genetic algorithm to solve the proposed Mixed-Integernon-Linear Programming (MINLP) model.

The rest of the paper is organized as follows. First, the problem is defined and formulated as a mathematical programming model. Secondly, a genetic algorithm is proposed to solve the MINLP model. The performance of the genetic algorithm is compared

with GAMS (Generalized Algebraic Modeling System) solver, and experimental results are presented. Finally, a small sample selected from the Tehran municipal project portfolio is used to describe the application of the model.

## 2. Problem definition

Consider an organization that pursues various strategic objectives and probably, has divided its territory into multiple districts. Municipalities and governmental organizations are examples. In such a context, usually there is a direct or indirect competition between departments and districts in receiving more funds; but financial resources and other organizational capabilities are limited. So we need a method for balanced project portfolio selection.

Strategic objectives are measured by indicators. We categorize indicators into two groups. The first group includes coverage indicators that are based on the distance of each region from the nearest corresponding facility. Regions could be considered as demand points and the distance from the nearest facility could be calculated. Facilities like fire and police stations are a few examples. Such facilities can cover multiple districts but the quality of service diminishes by increasing distance. We assume that the location of covering facilities has already been selected, and propose a model that decides which facilities and when will be built. The second group is general indicators in which the value of each indicator in each district is calculated based on the capacity, capability, or requirements of facilities and resources in that district. We call these two groups *coverage* and *general* indicators respectively. Table 1 lists some examples of indicators.

Projects are defined to establish covering facilities or provide capacities and capabilities that realize goals of indicators. Some indicators have a positive and more-is-better nature while the others have a negative

**Table 1.** Indicator examples.

Indicator type	Examples
General	Per capita municipally-funded cultural facilities and spaces
	Bike-friendly index
	Per capita parks and recreation rain barrels and cisterns per house
	Per capita indoor recreation facility space
	Per capita outdoor recreation facility space
	Rate of stormwater runoff
Coverage	Congestion severity index
	Distance from nearest fire station
	Distance from nearest police station
	Distance from nearest emergency service

and less-is-better nature. *Congestion severity index* and *urban air pollution of particulate matter* must be decreased but *per capita parks and recreation* and *per capita indoor recreation facility space* must be increased. Therefore a project could increase or decrease an indicator.

Selected projects are planned over a multi-period planning horizon. Each indicator has a baseline (current) and a target value in each region in each time-period. The projects are selected and planned to create a balanced achievement of indicator targets.

The goal programming approach is selected to handle the multi-objective nature of the problem. In goal programming, a multi-objective model turns into a single-objective model. Each objective takes a value as a goal and the model tries to achieve it, or minimize undesirable deviations from the goals.

### 3. Problem formulation

#### 3.1. Objective function

Usually, in goal programming models, the objective function is the total weighted deviations from the goals. Let  $j$  and  $k$  be index of districts and indicators respectively. In the simplest case, the objective function can be expressed as follows:

$$\min z = \sum_k \sum_j (\text{deviation of indicator } k \text{ in region } j \text{ from its goal}). \tag{1}$$

But this objective function does not differentiate between large and small deviations. To illustrate this point, we present a simple example. Assume that a city has two regions. There are two types of indicators: *park and recreation space per capita* and *municipally-funded cultural center per capita*. Assume that due to resource constraints, we only can select 2 projects out of the 4 proposed projects. In this example, the weight of the indicators and regions are considered equal. Data of projects and indicators are listed in Table 2.

If projects 2 and 1 or projects 2 and 4 are selected, total deviations of indicators from their goals will be 0.4 (0.2+0.0+0.1+0.1 and 0.3+0.0+0.1+0.0 respectively). This objective function did not differentiate between selecting project 1 and project 4, while it is observable

that the deviation of the indicator affected by project 1 from its target is so greater than project 4.

A usual idea for penalizing large deviations is squaring the deviations. For example, in statistical models, parameters are estimated so that the Sum of Squared Errors (SSE) is minimized. So the following function can be used:

$$\min Z \sum_{k=1}^2 \sum_{j=1}^2 (\text{deviation of indicator } k \text{ in region } j \text{ from its goal})^2. \tag{2}$$

In the aforementioned example, if projects 1 and 2 are selected, the value of the new objective function will be 0.06 but if projects 4 and 2 are selected, it will be 0.1; therefore, this objective function differentiates between large and small deviations, and project 1 will be preferred to project 4.

This objective function is balanced with regard to indicators, but not in terms of the regions. To demonstrate this point, again consider the previous example. The above objective function does not differentiate between the selection of projects 3 and 4 and the selection of projects 2 and 3 and does not take into account the balance of the regions. While it seems obvious that the selection of projects 2 and 3 should be better than selecting projects 3 and 4 (it promotes social justice). Therefore, the objective function is modified as follows:

$$\min z = \sum_{k=1}^2 \left( \sum_{j=1}^2 \text{deviation of indicator } k \text{ in region } j \text{ from its goal} \right)^2 + \sum_{j=1}^2 \left( \sum_{k=1}^2 \text{deviation of indicator } k \text{ in region } j \text{ from its goal} \right)^2. \tag{3}$$

With this objective function, if projects 3 and 4 are selected, the objective function is 0.26 but if projects 3 and 2 are selected, the objective function is 0.2. As a result, the balance of the regions was considered.

For the project portfolio to be balanced in terms of timing, we assume that for each indicator in each region in each time period of the planning horizon, a target is determined. So the objective function will be:

**Table 2.** Projects and indicators data for the illustrative example.

Project ID	Indicator	Region	Indicator target	Indicator baseline	Improve in indicator by project
1	Park and recreation space per capita	1	0.4	0.1	0.1
2	Cultural center per capita	1	0.2	0.1	0.1
3	Park and recreation space per capita	2	0.4	0.3	0.1
4	Cultural center per capita	2	0.2	0.1	0.1

$$\min z = \sum_t \sum_k \left( \sum_j d_{kjt} w_{kj} \right)^2 + \sum_t \sum_j \left( \sum_k d_{kjt} w_{kj} \right)^2, \tag{4}$$

in which  $d_{kjt}$  is the deviation of indicator  $k$  in region  $j$  in time period  $t$  from its target. Based on the type of indicator  $k$ , it will be equal to  $d_{kjt}^-$  (for more-is-better indicators) or  $d_{kjt}^+$  (for less-is-better indicators).

The parameter  $w_{kj}$  reflects the importance of indicator  $k$  in district  $j$ . This relative importance could be derived by considering two factors: the priority of indicator  $k$  (relative to other indicators), and the requirements or population of the district  $j$ . For example, in the case of ‘green space per capita’, we consider the priority of green space development relative to other organizational objectives, and the population of each region relative to the total population. In the case of transportation improvement, we consider the priority of transportation improvement relative to other organizational objectives, and the requirements of transportation improvement in each region relative to the city’s total requirements.

**4. Notations**

The following symbols are used in this paper:

- $i$  Index of the projects ( $i = 1, 2, \dots, N$ )
- $q, j$  Index of the districts
- $k$  Index of the goals (indicators)
- $K$  Set of the indicators
- $K_p$  Set of the general indicators
- $K_s$  Set of the coverage indicators
- $t$  Index of the periods

**Parameters**

- $a_{kj}$  The baseline (current state) of the indicator  $k$  in the region  $j$
- $B_t$  Total available budget in time period  $t$
- $c_i$  Cost of executing project  $i$  in each period
- $f_{kjq}$  The distance of region  $q$  from covering facility that will be established in region  $j$  related to indicator  $k$
- $g_{kjt}$  The target of indicator  $k$  in region  $j$  in time period  $t$
- $h_{kji}$  A binary parameter that equals 1 if the project  $i$  affects indicator  $k$  in the region  $j$ , and 0, otherwise
- $H$  Set of prerequisite projects ( $i', i$ ).  $i'$  is prerequisite for  $i$

- $r_{kji}$  Improvement in indicator  $k$  in region  $j$  due to the implementation of project  $i$
- $S_p$   $p$ th set of incompatible projects.  $S$  is a superset
- $v_i$  The duration of project  $i$  (in time periods)
- $w_{kj}$  The weight of the indicator  $k$  in the region  $j$

**Decision variables**

- $d_{kjt}$  The deviation of indicator  $k$  in region  $j$  in time period  $t$  from its target. It is equal to  $d_{kjt}^+$  or  $d_{kjt}^-$
- $d_{kjt}^-$  The negative deviation of indicator  $k$  in region  $j$  in time period  $t$  from its target
- $d_{kjt}^+$  The positive deviation of indicator  $k$  in region  $j$  in time period  $t$  from its target
- $m_{it}$  A binary variable that equals 1 if the implementation of project  $i$  continues in time period  $t$ , and 0 otherwise
- $x_{it}$  A binary variable that equals 1 if project  $i$  ends in time period  $t$ , and 0, otherwise
- $Y_{kjq}$  A binary variable that equals 1 if the closest covering facility that affects indicator  $k$  in region  $j$  in time period  $t$ , locates in region  $q$ , and 0, otherwise
- $P_{iut}$  A binary variable that equals 1 if project  $i$  is implementing in period  $u$  and will be finished in period  $t$ , and 0, otherwise;

**5. Final model**

Final mathematical model can be written as follows:

$$\min z = \sum_{t=1}^T \sum_{k=1}^K \left( \sum_{j=1}^J d_{kjt} w_{kj} \right)^2 + \sum_{t=1}^T \sum_{j=1}^J \left( \sum_{k=1}^K d_{kjt} w_{kj} \right)^2, \tag{5}$$

$$a_{kj} + \sum_{t'=1}^t \sum_{i=1}^n r_{kji} x_{it'} + d_{kjt}^- - d_{kjt}^+ = g_{kjt} \quad \forall k \in K_p, \forall t, j, \tag{6}$$

$$\sum_q Y_{kjq} = 1 \quad \forall k \in K_s, \forall t, j, \tag{7}$$

$$Y_{kjqt} \leq \sum_{t'=1}^t \sum_{i=1}^n h_{kqi} x_{it'} \quad \forall k \in K_s, \forall t, q, j, \quad (8)$$

$$\sum_q Y_{kjqt} f_{kjq} + d_{kjt}^- - d_{kjt}^+ = g_{kjt} \quad \forall k \in K_s, \forall t, j, \quad (9)$$

$$\sum_{t=1}^T m_{it} = v_i \sum_{t=1}^T x_{it} \quad \forall i, \quad (10)$$

$$\left( \sum_{t'=t-v_i+1}^t m_{it'} - v_i \right) x_{it} \geq 0 \quad \forall i, v_i \leq t \leq T, \quad (11)$$

$$x_{it} = 0 \quad \forall i, 1 \leq t \leq v_i - 1, \quad (12)$$

$$\sum_{i=1}^n c_i m_{it} \leq B_t \quad \forall t = 1, \dots, T, \quad (13)$$

$$\sum_{t'=1}^t x_{it'} \geq \sum_{t'=1}^t x_{it'} \quad \forall t, (i', i) \in H, \quad (14)$$

$$\sum_{i \in S_p} \sum_{t=1}^T x_{it} \leq 1 \quad p = 1, \dots, |S|, \quad (15)$$

$$\sum_{t=1}^T x_{it} \leq 1 \quad \forall i, \quad (16)$$

$$x_{it} = 0 \text{ or } 1 \quad \forall i, t, \quad (17)$$

$$d_{kjt}^-, d_{kjt}^+ \geq 0 \quad \forall k, t, j, \quad (18)$$

$$Y_{kjqt} = 0 \text{ or } 1 \quad \forall k, j, q, t. \quad (19)$$

The objective function (5) minimizes the deviations from the goal of each indicator in each region in each time period. Constraints (6) indicate the deviation of each general indicator from its predetermined goal. Constraints (7) to (9) are related to coverage indicators. Constraints (7) ensure that only one facility can be considered as the nearest facility to each region. Constraints (8) guarantee that the closest region to the region under consideration is the region where the covering project is implemented. In Constraints (9), the phrase  $\sum_q Y_{kjqt} f_{kjq}$  shows the distance between the region  $j$  and the nearest facility. This constraint measures the deviation of the minimum distance between each region and established coverage facilities relative to a predetermined goal for each coverage indicator. Constraints (7) to (9) are written for each coverage indicator in each time period in each region. Constraints (10) and (11) guarantee that projects implementation periods and completion periods are synchronized. Constraints (12) guarantee that each project is finished within the

planning horizon. In each public organization, the most important limiting factor for project selection is the organizational budget. This constraint is shown in Constraint (13), which is related to the budget of all projects in each period. In Constraints (14), the dependencies between the projects are shown. These constraints guarantee that the prerequisite project  $i'$  is implemented prior to or concurrent with the dependent project  $i$ . Constraints (15) prohibit the simultaneous selection of conflicting projects. At most one project could be selected from each incompatible projects set. Constraints (16) ensure that each project (if selected) can only be finished once. Constraints (17), (18), and (19) represent the non-negativity and integrality of decision variables.

### 6. Linearization

The presented mathematical model in the previous section is a mixed-integer non-linear programming model due to the existence of nonlinear terms in the objective function and one of the constraints. Multiplication of two binary variables in Constraint (11) makes it non-linear. The nonlinear constraint could be converted into linear by defining a new variable,  $P_{iut}$  which substitutes  $m_{it'} x_{it}$ . Let  $P_{iut}$  be a binary variable that equals 1 if project  $i$  is implementing in period  $u$  and will be finished in period  $t$ . So Constraint (11) can be rewritten as follows:

$$\sum_{u=t-v_i+1}^t P_{iut} - v_i x_{it} \geq 0 \quad \forall i, v_i \leq t \leq T. \quad (20)$$

But the following constraints must be added to the model:

$$P_{iut} \leq m_{iu} \quad \forall i, \forall t, \quad u = 1, \dots, T, \quad (21)$$

$$P_{iut} \geq x_{it} \quad \forall i, \forall t, \quad u = 1, \dots, T, \quad (22)$$

$$P_{iut} \geq m_{iu} + x_{it} - 1 \quad \forall i, \forall t, \quad u = 1, \dots, T, \quad (23)$$

$$P_{iut} = 0 \text{ or } 1 \quad \forall i, \forall t, \quad u = 1, \dots, T. \quad (24)$$

### 7. Solution approach

In the previous section, Constraint (11) was converted to linear form, but due to the nonlinearity of the objective function and the integrality of variables, it is difficult to obtain an exact solution for the proposed mathematical model. One of the common approaches to solving complex problems is to use metaheuristic methods to obtain a good solution in a meaningful time. Heuristic and metaheuristic methods under such conditions can provide a reasonable balance between the quality of the solution and the solution time.

Evolutionary Algorithms (EA) are stochastic

population-based metaheuristics that have been successfully applied to many real and complex problems. They are the most studied population-based algorithms [25]. Genetic Algorithms (GA) are a very popular class of EAs and a powerful search technique applied to optimization problems [26]. The GA starts by generating an initial population. Then, a set of chromosomes is selected and these chromosomes evolve by crossover and mutation operations. This process will continue until a stop criterion is met.

**Chromosome representation:** The structure of the proposed mathematical model shows that  $x_{it}$  is the main decision variable. If  $x_{it}$  is given, other variables could be calculated. So only  $x_{it}$  is considered in chromosome design. Each chromosome is defined as a two-dimensional matrix each element of which can be zero or one. Each row represents a project and each column represents a time period. Each gene of the chromosome (or each cell of the matrix) indicates that whether the project  $i$  in period  $t$  ends or not. Having this decision variable, the rest of the decision variables can be obtained through the model constraints, and the value of the objective function can be calculated.

**Constraint handling:** In this model, the violation of some Constraints ((6) to (12), and (16)) is maintained by generating the proper initial population and performing the proper evolutionary process. The feasibility of other Constraints ((13), (14), and (15)) is kept by adding a penalty term to the objective function.

**Crossover:** Crossover is the process whereby each part of two chromosomes (called parents) forms the characteristics of a new chromosome (child). In this research, two types of crossovers are used, namely single-point crossover and uniform crossover. When two chromosomes are selected as parents, one of these crossovers is selected randomly. In the single-point

crossover, a random row is selected as a crossover point. Each child inherits all rows from one of the parents up to the crossover point and other rows from another parent. In the uniform crossover, the child randomly inherits each row of the chromosome from one of the parents.

**Mutation:** Mutation operation generates new solutions to avoid algorithm from trapping in a local optimum. First, mutation operation randomly selects a row of the selected chromosome. If the selected project is executed, this operator randomly changes the time period of execution or cancels the project execution. But if the selected project is not executed, the mutation operator randomly selects a period, and the selected project ends in that time period.

## 8. Experimental results

In this section, the efficiency of the proposed genetic algorithm in terms of solution quality and run time is investigated. For this purpose, eight test problems are solved by proposed GA and obtained results are compared with solutions obtained through solving problems with a GAMS solver. The structure of test problems and obtained results are reported in Tables 3 and 4 respectively. The results obtained by GAMS are reported separately for non-linear and linear constraints.

For the smallest test problem, the objective functions of the three methods are the same. This shows the validity of implemented algorithms. For other test problems, the proposed genetic algorithm has a better performance in terms of solution time and quality. As Table 4 shows, when problem size grows, the run time of GAMS increases rapidly (44864 seconds for 55 projects). According to obtained results, in the model with linear constraints, the GAMS solver can find better solutions in a shorter time compared with the model with non-linear constraints.

**Table 3.** Structure of test problems.

Test problem	Problem size			
	Projects	Districts	Indicators	Periods
1	15	6	4	3
2	20	7	5	3
3	25	8	5	4
4	30	9	6	5
5	40	10	7	6
6	45	11	7	7
7	50	11	8	7
8	55	12	8	8

**Table 4.** Computational results of the test problems.

Test problem	GAMS						
	Non-linear constraints		Linear constraints		Genetic algorithm		
	Objective function	Run time	Objective function	Run time	Objective function	Run time	GAP
1	1.3036	11.56	1.30360	15.31	1.3036	20.66	0%
2	0.08046	23.18	0.07906	33.89	0.07905	27.10	2%
3	0.41445	60.34	0.40203	150.81	0.40053	50.09	3%
4	0.31912	340.25	0.31603	526.30	0.31311	80.30	2%
5	0.7961	813.10	0.79350	1167.83	0.79079	164.65	1%
6	0.7976	1645.48	0.79414	2054.78	0.79341	245.98	1%
7	0.68806	28641.47	0.66602	3512.46	0.66184	335.15	4%
8	0.97085	44864.47	0.96724	5316.67	0.96715	411.65	1%

### 9. Numerical example

In this section, the application of the model is described with a subset of Tehran municipality candidate projects. Tables 5 and 6 lists the available budget for each period and the information required for candidate projects. The amount of budgets are expressed in terms of ten million Iranian Rials. Table 6 shows a list of candidate projects that includes 15 projects. According

**Table 5.** Available budget.

Time period	Available budget
1	5000
2	5000
3	5000

to Table 6, projects 4 and 9 are incompatible and could not be selected together.

Table 7 demonstrates the distance between urban areas, and Tables 8 and 9 illustrate all the other information relating to the regions and indicators. It must be pointed out that indicators 2 and 4 are coverage, while indicators 1 and 3 are general types.

**Table 7.** Distance between urban areas (km).

Region	1	2	3	4	5	6
1	–	15.6	6.9	14	19	13.2
2	–	–	10	19.4	4.3	8.8
3	–	–	–	13.6	12.7	7.4
4	–	–	–	–	22	17.1
5	–	–	–	–	–	12.4
6	–	–	–	–	–	–

**Table 6.** Candidate projects information.

Project number	Budget	Duration	Prerequisite project	Incompatible project
1	800	1	–	–
2	780	1	–	–
3	2800	2	–	–
4	2000	1	–	9
5	1400	1	–	–
6	2000	1	1	–
7	1500	2	3	–
8	1000	1	11	–
9	1500	1	–	4
10	2450	1	–	–
11	1200	1	–	–
12	2300	2	–	–
13	1000	1	10	–
14	3600	1	–	–
15	2860	2	–	–

**Table 8.** Information of regions and indicators.

Region	Indicator	Indicator weight	Indicator baseline	Region population ratio	$w_{kj}$	Indicator target		
						Period 1	Period 2	Period 3
1	1	0.2	20	0.134332	0.027	22	24	25
	2	0.3	–	0.134332	0.040	14	13	12
	3	10	0.35	0.134332	1.3	0.45	0.55	0.6
	4	0.3	–	0.134332	0.040	11	10	8
2	1	0.2	20	0.193463	0.039	22	24	25
	2	0.3	–	0.193463	0.058	14	13	12
	3	10	0.3	0.193463	1.9	0.45	0.55	0.6
	4	0.3	–	0.193463	0.058	11	10	8
3	1	0.2	18	0.096014	0.019	22	24	25
	2	0.3	–	0.096014	0.029	14	13	12
	3	10	0.3	0.096014	0.96	0.45	0.55	0.6
	4	0.3	–	0.096014	0.029	11	10	8
4	1	0.2	19	0.263267	0.053	22	24	25
	2	0.3	–	0.263267	0.079	14	13	12
	3	10	0.25	0.263267	2.6	0.45	0.55	0.6
	4	0.3	–	0.263267	0.079	11	10	8
5	1	0.2	18	0.242625	0.049	22	24	25
	2	0.3	–	0.242625	0.072	14	13	12
	3	10	0.15	0.242625	2.4	0.45	0.55	0.6
	4	0.3	–	0.242625	0.072	11	10	8
6	1	0.2	18	0.070298	0.014	22	24	22
	2	0.3	–	0.070298	0.021	14	13	12
	3	10	0.20	0.070298	0.7	0.45	0.55	0.6
	4	0.3	–	0.070298	0.021	11	10	8

To illustrate the effect of the proposed objective function, we solved the above-mentioned example considering four different objective functions. Table 10 shows the final solutions. Columns with ‘the proposed objective function’ header, show the final solution with the proposed objective function. Projects 3, 6, 7, 9, 12, and 15 are not selected. Others are planned in such a way that they could be finished in periods one to three with an objective function of 33.0296. Indicators 2 and 4 are coverage indicators. As shown in Table 10, only projects 5 and 13 are selected for indicator 2, that is, the facilities are built in districts 6 and 5. For indicator 4, projects 2, 8, and 10 are selected, which means that facilities are constructed in districts 4, 2, and 5. As

shown in this example, due to resource constraints, all of the facilities have not been constructed.

In addition to the main model, the example was solved by three other alternative objectives:

1. **Linear objective function.** A linear objective function is usually used in the objective programming models:

$$\min z = \sum_{t=1}^T \sum_{k=1}^K \left( \sum_{j=1}^J d_{kjt} w_{kj} \right). \tag{25}$$

Solving the model by this objective creates a solution that its equivalent objective function in the

**Table 9.** Effect of projects on indicators.

Region	Indicator	Project	Indicator improvement by implementing project
1	1	$X_{11}$	2.5
	4	$X_8$	–
2	2	$X_3$	–
	4	$X_7$	–
3	1	$X_1$	2
	2	$X_{12}$	–
	4	$X_6$	–
4	3	$X_{14}$	0.1
	4	$X_2$	–
5	1	$X_9$	2
	2	$X_{13}$	–
	3	$X_4$	0.1
	4	$X_{10}$	–
6	2	$X_5$	–
	3	$X_{15}$	0.1

**Table 10.** Solution of the proposed example considering different objective functions.

Project	Region	Indicator	Proposed objective function			Linear objective function			Region balancing			Last period balancing		
1	3	1	0	1	0	1	0	0	0	1	0	0	1	0
2	4	4	1	0	0	1	0	0	1	0	0	0	1	0
3	2	2	0	0	0	0	0	0	0	0	0	0	0	0
4	5	3	0	1	0	0	1	0	0	1	0	0	1	0
5	6	2	1	0	0	1	0	0	1	0	0	1	0	0
6	3	4	0	0	0	1	0	0	0	1	0	0	0	0
7	2	4	0	0	0	0	0	0	0	0	0	0	0	0
8	2	4	0	1	0	0	0	0	0	0	0	0	0	1
9	5	1	0	0	0	0	0	0	0	0	0	0	0	0
10	5	4	1	0	0	0	1	0	1	0	0	1	0	0
11	1	1	0	1	0	0	0	1	0	0	0	0	1	0
12	3	2	0	0	0	0	0	0	0	0	0	0	0	0
13	5	2	0	0	1	0	0	0	0	0	1	1	0	0
14	4	3	0	0	1	0	0	1	0	0	1	0	0	1
15	6	3	0	0	0	0	0	0	0	0	0	0	0	0
Objective function			33.0296			33.2313			33.2981			37.3805		

main model is 33.2313 and project 6 is selected instead of projects 8 and 13 and projects 1, 10, and 11 are planned in different periods. This function does not differentiate between small and large deviations.

- Region balancing.** Another alternative is the sum of squared deviations by region:

$$\min z = \sum_{t=1}^T \sum_{k=1}^K \left( \sum_{j=1}^J d_{kjt} w_{kj} \right)^2. \tag{26}$$

This objective creates a solution that its equivalent objective function in the main model is 33.2981 and the timing of projects is shown in Table 10. The result is not balanced in terms of indicators.

- Last period balancing.** If we ignore the timing of projects as a balancing factor, the objective function comprises the sum of squared deviations at the end of the planning horizon:

$$\min z = \sum_{t=T}^T \sum_{k=1}^K \left( \sum_{j=1}^J d_{kjt} w_{kj} \right)^2$$

$$+ \sum_{t=T}^T \sum_{j=1}^J \left( \sum_{k=1}^K d_{kjt} w_{kj} \right)^2. \quad (27)$$

This objective creates a solution that its equivalent objective function in the main model is 37.3805 and the timing of projects is shown in Table 10. The result is not balanced in terms of the time factor.

## 10. Conclusion and future work

This paper proposes a project portfolio selection model with two main contributions. It suggests a way for balancing urban and public sector projects portfolio in terms of factors such as timing, districts, and objectives. On the other hand, in the set covering literature, there are enormous models for optimum selection of facility locations; but when there are several types of facilities (like fire stations, emergency services, and health care) and available capacity and resources are limited, a model is needed to optimally decide on prioritization and planning of the facilities construction. This paper proposes such a model using a goal programming approach. The construction of each facility is considered as a project and the presented model specifies which projects must be implemented in each time period. To illustrate the performance of the model, the data of several projects relating to the Tehran municipality were considered as an example.

This research presents some assumptions that could be extended in future studies. The first is to assume that the coverage facilities have already been positioned, and only the priority and timing for the construction of these facilities are problematic. In some cases, for better service availability, temporary facilities would be opened in locations different from those of permanent facilities. Therefore there will be a trade-off between service availability and the cost of opening and closing temporary facilities. The second assumption is that the implementation cost of each project could not be distributed uniformly over its executing period. Finally, some projects could create revenues for the municipality or government. Thus these projects could be a source of funds for other projects.

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