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Identifying and Investigating the Simultaneous Effect of Effective Parameters in the Resources Allocation for Construction Projects and Optimizing Using Meta-Heuristic Algorithms

Abbas Rashidi[1], Alireza Lork*[2], Babak Aminnejad[3]

1: Department of Civil Engineering, Kish International Branch, Islamic Azad University, Kish Island, Iran

Email: rashidicivil.2006@gmail.com

2: Department of Civil Engineering, Karaj Branch, Islamic Azad, University, Karaj, Iran

Email: lork@iau.ac.ir

3: Department of Civil Engineering, Roudehen Branch, Islamic Azad University, Roudehen, Iran

Email: aminnejad@riau.ac.ir

Abstract: - Addressing the construction projects with decreasing execution time and gaining the optimal implementation modes and start time for all sub-activities under priority relationships, logical relationships and continuity in resource allocation, is one of the challenges of experts in this field. Solving this type of problem is one of the problems in construction projects, because resource continuity constraints and different kinds of time limitations should be reflected in the optimization procedure. Therefore, in this research, we introduce a new bi-objective model for optimal allocation of resources to project activities and simultaneously examine the effective factors including time and cost on this model. The purpose of this proposed model is to decrease project duration, while also decreasing various resource consumption. To solve the proposed bi-objective problem, multi-objective evolutionary approaches including NSGA-II and NRGA are applied. At first, the parameters of these algorithms are calibrated by Taguchi method and finally they are utilized to solve the model. In order to quantify the parameters of the proposed model, a case study related to the waste incineration plant in Iran was presented and for further comparisons, several numerical examples in larger dimensions were used. These algorithms were compared by several standard multi- objective measure metrics common in this field and the results were analyzed by statistical methods. Finally, the results showed the superior performance of the NSGA-II method. The outputs of this approach were explained for a Pareto solution selected according to experts' opinions.

Keywords: meta-heuristic algorithm; resource allocation; construction project scheduling; waste incineration plant.

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1. Introduction

The most important principle in optimizing the project managment and control process is to reduce the impact of constraints on the project during its implementation. In general, projects have three major limitations in achieving their goals [1]. These limitations are: restrictions on the time of activities and consequently the final time of the project, restrictions on the using project resources, and restrictions on the implementation of special activities. Since the simultaneous effect of constraints can cause significant deviations in achieving project goals, if possible, by balancing these constraints, efforts should be made to optimize the time, cost and quality of project activities [2]. Nowadays, the need for proper planning in order to accurately estimate the time and cost of the project and the amount of resources required in a project is clear that have a direct impact on the implementation, management and proper operation of projects such as construction of dams and buildings. In general, managing and planning the activities and resources required in a project requires various analyzes, one of which is the correct modeling and forecasting of the cost and time of the project. Achieving this goal contributes significantly to the optimal management of the project and decision-making in specific situations [3].

The issue of project planning and scheduling is becoming more important every day. In an environment where the competition of companies is getting closer day by day and small differences in the presentation of prices in tenders lead to success or failure in the tender, presenting a program that is consistent with the facts and can contain all the economic facts in a project model is very important [4]. A comprehensive program has the ability to use the cost-time relationship in a project to consider the necessary changes in the cost and time of resources and provide appropriate solutions to users so that they can make a proper estimate before the project have the time and cost of implementation and the amount of resources required in the project [5].

All human actions in nature are the result of his decisions and his knowledge of all possible options and possible outcomes based on these types of activities. Given the type of problem and its possible complexity, it seems practically impossible to accurately predict the most desirable answer. In practice, the decision- making process is usually associated with several different, non-equal and often non-directional objective functions. This means that the process of evaluating different functions cannot be essentially the same, and in many cases, the value of one objective function cannot be increased without decreasing the value of the other objective function. Therefore, for the final decision, there is a need for a balance between different goals, and the manner of this compromise is very important in decision making [6,7]. In this regard, risk, profit, cost and social interests can have a significant impact on this compromise that such issues are known as multi-criteria decision-making issues [8].

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Meta-heuristic algorithms are the search and optimization methods based on natural evolutionary principles. These algorithms allow a population of large numbers of individuals selected under special rules to optimize the fitness function during an evolutionary process. These algorithms have advantages over other optimization methods such as optimizing continuous or discrete variables with much more complex objective functions, using potential transfer rules instead of definite rules, and the ability to work with a large number of variables [9,10]. For the first time, Feng et al. [11] used the meta-heuristic algorithm in solving the balanceing time-cost problem and hegazy [12] in solving the resources leveling and allocation.

problem. In their modeling, they pursued single-objective optimization and considered the decision-maker's preferences in choosing the option only by weighting the time and cost parameters.

Given the importance of these issues, we seek to cover all of these issues in a comprehensive study. Therefore, in this research, we introduce a new bi-objective model for optimal allocation of resources to construction project activities and simultaneously examine the effective factors including time and cost on this model. The aim of this proposed model is to minimize project completion time, while also minimize various resource consumption. To solve the formulated bi-objective mathematical problem some multi- objective evolutionary approaches including non-dominated ranking genetic algorithm (NRGA) and non- dominated sorting genetic algorithm (NSGA-II) are applied. At first, the parameters of these algorithms are calibrated by Taguchi method and finally they are utilized to solve the problem. In order to quantify the parameters of the proposed model, a case study related to the waste incineration plant in Iran is presented and for further comparisons, several numerical examples in larger dimensions are used. These algorithms are compared by several standard multi-objective criteria common in this field and the results are analyzed by statistical methods. Finally, according to the performance of the algorithms, one of them is selected as the most desirable solution and is selected for a Pareto front presentation according to the experts.

In the following, the second section examines the research background and the basics of literature. The third section describes the proposed mathematical model and problem. Also, the fourth section describes the proposed meta-heuristic algorithms and the fifth section describes the case study and the results including the problem under study, population size, probability of crossover and mutation, comparison of algorithms and computational results. Finally, the sixth section discusses the conclusions and perspectives.

2. Research Background

After explaining the necessity of conducting research, it is time to present the research background and related issues. Therefore, in this section, we review the background of

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research. It should be noted that in order to collect this researches, international publishers and journals, websites, and library centers have been used.

Firstly, Feng et al. [11] utilized the genetic algorithm in 1997 to solve the time-cost balance problem as a single objective model. By demonstrating the choice of time and cost of each activity in each gene on each chromosome, they demonstrated the ability to use genetic algorithms to solve the time-cost balance problem. They were also able to prove the capability of this algorithm by providing a convergence process towards the optimal solution. They introduced the use of the Pareto front in solving the problem as a multi- objective model. Then in 2000 they expanded their model by considering simulation time and cost parameters using simulation methods. Initially, they showed the ability of the genetic algorithm to achieve the optimal solution by considering the time-cost relationship linearly as well as improving the convergence process of the genetic algorithm. Obviously, they considered their objective function only as costs minimizing [13]. Using the previous results, Zheng et al. [14] for the first time compared the results of solving the cost-time balance problem in the form of the adaptive weight adjustment (AWA) and the modified adaptive weight adjustment (MAWA) that both methods were single-objective. Based on their results, the rate of convergence towards the optimal response in the AWA method was higher than MAWA. Then in 2005 they expanded their model using fuzzy logic by assigning the membership function to time and cost parameters [15].

Zareei [16] noted that creation of a large-scale biogas factory and its project managment require numerous organized processes with different times and includes many dependencies. For that reason, they focused on the presentation of scheduling and planning for the examination of the biogas factory building project by means of the critical path (CPM) technique. Also, the obtained outputs showed that the minimum completion time of the construction of a 50 cubic meter biogas factory with a stable cupola in studied country will be 38 weeks if the project stages are not delayed. A network is also designed for this project to demonstrate the interactions of activities. Kadri and Boctor [17] also addressed the project schedule with limited resources with transfer time. They assumed that prerequisite was not allowed and that the start-up relationship was zero with a delay. It is also assumed that the duration of implementation and the time of transfer of resources of tasks are recognized and decisive. The goal is to select the start time for each project task to minimize project duration while realizing priority relationships, resource availability, and resource transfer time restraints. They proposed a novel version of crossover operator for applied genetic algorithm to solve the problem. This experiment, which has been performed in many cases, displays that the suggested algorithm achieves better than some previously available solutions.

In the field of mathematical methods for resource leveling and allocation, Gavish and Pirkul [18] optimized the resource leveling and allocation problem using dynamic algorithmic

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programming. They provided effective solutions to the problem of general multiple resource allocation. In this research, various limitations of liberalization have been studied and the theoretical relationships between these liberalizations have been mentioned. Rules for reducing the size of the problem have been discussed and shown to be effective through computational experiments. Meta-heuristic methods and an efficient branch and bound method have been developed. But as Hegazy [12] points out, none of these methods are suitable for solving real and complex problems. On the other hand, mathematical methods have been used to solve these problems, which are based on the characteristics of activities such as minimum free float. These methods are simple and for computer programming. Davis and Patterson [19] also used the methods of minimum total float and the earliest start-up time in their models. Despite all the advantages mentioned, these methods cannot guarantee the achievement of optimal solutions. It also cannot be used in complex and large issues. Servranckx and Vanhoucke [20] also examined the issue of resource-limited project planning with substitute subgraphs. In this planning issue, there are alternative ways to perform a subset of tasks which depend to work packages. A substitute implementation mode should be chosen for each work package, and consequently the nominated tasks must be planned in the project configuration. The main characteristic of this study is the arrangement of altered kinds of substitute subgraphs in a general classification matrix according to the dependencies among the options in the project configuration. Because this framework did not support problem-specific datasets, they generated several numerical examples by means of a well- known project network. Moreover, they used a tabu search meta-heuristic algorithm which applies the suggested classification matrix information to help the exploration process toward a quality solution. Furthermore, they showed the effect of various problem parameters on the quality of the solution and analyzed the effect of the characteristics of distinct sources of alternative options in the choice procedure. On the other hand, a review of related research is provided in Table 1. Considering the total research works done in the field of application of meta-heuristic algorithm in the optimizing time, cost, and resource leveling and allocation, it is obvious that due to the dependence of the duration of each activity on its direct cost, the direct cost of each activity depended on the number of consumption resources of the relevant activity in a construction project. Finally, can developed a multi-objective model in which, while leveling resources, gained points from the Pareto front that represented the least cost and time.

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Table 1. A review of the literature related to this research

Reference	Year	Model type	Model features: Uncertainty	Time	Interruption	Cost	Resource coherence	Prerequisite	Method	Case study
[11]	1997	SO		✓		✓			Meta-heuristic	Numerical example
[13]	2000	SO	✓	✓		✓			Meta-heuristic	Numerical example
[14]	2004	SO		✓		✓			AWA, MAWA	Numerical example
[15]	2005	SO	✓	✓		✓			Fuzzy logic	Numerical example
[16]	2018	SO		✓				✓	CPM	Biogas plant
[17]	2018	SO		✓			✓	✓	Meta-heuristic	Numerical example
[18]	1999	SO				✓	✓		Meta-heuristic	Numerical example
[19]	1975	SO		✓			✓	✓	Heuristic	Numerical example
[20]	2019	SO				✓	✓	✓	Meta-heuristic	Numerical example
[21]	2020	SO		✓			✓	✓	Exact method	Freight planning
[22]	2021	MO		✓			✓	✓	FAHP-MCGP	Internal audit
[23]	2021	MO	✓	✓			✓	✓	Meta-heuristic	Numerical example
[24]	2021	SO		✓		✓	✓	✓	Exact method	Numerical example
[25]	2021	SO		✓		✓			Meta-heuristic	Numerical example
[26]	2021	MO		✓			✓	✓	Meta-heuristic	Numerical example
[27]	2021	SO		✓		✓		✓	Exact method	Numerical example
[28]	2021	MO	✓				✓	✓	Meta-heuristic	Numerical example
[29]	2022	SO		✓		✓		✓	Meta-heuristic	Numerical example
This work	-	MO		✓	✓	✓	✓	✓	Meta-heuristic	Waste incineration plant
SO: single objectiveMO: multi-objective										

In the third section, the model will be introduced in full detail and then in a case study, the application and results of the model will be examined. The main innovation in this research is considering costs and other resources in the scheduling and resources allocation problems simultaneously in a model and its application in a case study.

3. Problem Description

As stated in the previous sector, the purpose of this research is to develop an optimization model for time and resource allocation using meta-heuristic algorithms. In this research, the goal is to meet the objective function while minimizing time and resources simultaneously. The main innovation in this research is considering the genetic algorithm method in time analysis and resource allocation, which simultaneously optimizes time and resource parameters using a multi-objective model by NSGA-II and NRGA.

Power System Technology
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3.1. Proposed mathematical model

In this section, we introduce the proposed bi-objective model for the optimal allocation of resources to construction project activities and examine both the effective factors of time and cost on this model. The following are some of the model assumptions:

- I activity and J unit are assumed for a construction project.
- Sub-activities a11 and aIJ denote the beginning and end of the project, individually.
- The sequence of all activities are fixed from unit 1 to unit J, and the hard logic is assumed for them.
- Ki reoresents the variable implementation mode of activity i and all of its related sub-activities should be executed in the similar mode.
- All pair of activities (i, l) in sets of E(FF), E(FF), E(SF), and E(SS) must meet the least time limit of FF, FS, SF, and SS, individually. It should be noted that lth activity is performed after ith activity.
- Activities can also be divided into two groups. As any activity associated with w1 is permitted to interrupt, while there is no permission for interrupt in activities associated with w2.
- There are several types of resources available that each activity needs to run and these resources must be optimally allocated between activities.

Indices, sets, and parameters:

i, l=1,2,…, I	Indicates the index of activities
j=1,2,…, J	Represents the index of units of each activity
k=1,2,…, K_i	Indicates the variable execution modes of all sub-activities of each activity
f=1,2,…, F	Indicates the index of resources
$w_1 \in I$	A set of activities in which an activity is allowed to interrupt
$w_2 \in I$	A set of activities in which each activity must be performed without interruption
a_{ij}	Indicates the sub-activity related to the activity i under unit j
d_{ijk}	Indicates the duration time of sub-activity a_{ij} in mode k
t_{il}	Indicates the delay time between activities i and its next activity (l)
$Rmax_f$	Maximum amount of resource f available for allocation between activities
$Rneed_{if}$	The minimum amount of resource f required for allocation to activity i

Power System Technology
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Decision variables:

s_{ij}	Indicates the starting time of the sub-activity a_{ij}
x_{ik}	It is equal to 1 if activity *i* is performed under mode *k*, otherwise, it is zero
r_{ifk}	The amount of resource *f* allocated to activity *i* under mode *k*

After introducing the components of the model including assumptions, indices and sets, parameters, and decision variables, the proposed model is formulated as follows.

Objective function:

$$Min\, Z_1 = S_{IJ} + \sum_{k=1}^{K_i} x_{Ik} \times d_{IJk} \quad (1)$$

$$Min\, Z_2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{f=1}^{F}\sum_{k=1}^{K_i} (r_{ifk} \times S_{ij}) \quad (2)$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K_i} r_{ifk} \le R_f^{max} \qquad \forall f \in F \quad (3)$$

$$\sum_{k=1}^{K_i} r_{ifk} \ge R_{if}^{need} \times \sum_{k=1}^{K_i} x_{ik} \qquad \forall f \in F, i \in I \quad (4)$$

$$S_{ij} + \sum_{k=1}^{K_i} x_{ik} \times d_{ijk} \le S_{i(j+1)} \qquad \forall i \in w_1, j = 1,2,\ldots, J-1 \quad (5)$$

$$S_{ij} + \sum_{k=1}^{K_i} x_{ik} \times d_{ijk} = S_{i(j+1)} \qquad \forall i \in w_2, j = 1,2,\ldots, J-1 \quad (6)$$

$$S_{ij} + t_{il} \le S_{lj} \qquad \forall (i,l) \in E(SS), j \in J \quad (7)$$

$$S_{ij} + t_{il} \le S_{lj} + \sum_{k=1}^{K_l} x_{lk} \times d_{ljk} \qquad \forall (i,l) \in E(SF), j \in J \quad (8)$$

$$S_{ij} + \sum_{k=1}^{K_i} x_{ik} \times d_{ijk} + t_{il} \le S_{lj} \qquad \forall (i,l) \in E(FS), j \in J \quad (9)$$

$$S_{ij} + \sum_{k=1}^{K_i} x_{ik} \times d_{ijk} + t_{il} \le S_{lj} + \sum_{k=1}^{K_l} x_{lk} \times d_{ljk} \qquad \forall (i,l) \in E(FF), j \in J \quad (10)$$

$$\sum_{k=1}^{K_i} x_{ik} = 1 \qquad \forall i \in I \quad (11)$$

$$x_{ik} \in (0,1) \qquad \forall i \in I, k \in K_i \quad (12)$$

$$S_{ij}, r_{ifk} \ge 0 \qquad \forall f \in F, i \in I, k \in K_i \quad (13)$$

Power System Technology
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The objective function (1) tries to minimize the project time by finding the optimal implementation modes and start time (interruption policies) for all sub-activities. The objective function (2) tries to minimize the allocation of resources between activities that the necessary constraints for the minimum resource needs of each activity is met. This type of goal is used when the employer emphasizes the reduction of resource consumption time where rif is the number of consumed resources type f for activity i.

Constraint (3) indicates that the total resources allocated to activities should not exceed the maximum resources available for allocation. On the other hand, constraint (4) indicates that if activity i is to be executed using mode k, the minimum required amount of source f must be allocated to it. Constraints (5) and (6) ensure that all activities are performed in a fixed sequence from unit 1 to unit J and do not break the specified resource coherence restriction. Therefore, any activity associated with w1 is permitted to stop, while activities associated with w2 not able to interrupt executing. Limitations (7) to (10) guarantee the limits of the priority relationship between activities. Limitation (11) confirms that exactly one implementation mode is selected for each activity. Restriction (12) shows that the decision variable xik is binary. Constraint (13) also indicates non-negative variables.

3.2.Backward controlling segments method

If in the control path the backward controller ($A-$) and forward controller ($A+$) are considered, then the controller constraint can be formed as $\bar{C}$. Therefore, Equation (14) estimates the project duration using these properties.

$$T = \sum_{a_{ij} \in A^+} d_{ij} - \sum_{a_{ij} \in A^-} d_{ij} + \sum_{(i,l) \in C} t_{il} = \sum_{a_{ij} \in A^+} \sum_{k=1}^{K_i} x_{ik} \times d_{ijk} - \sum_{a_{ij} \in A^-} \sum_{k=1}^{K_i} x_{ik} \times d_{ijk} + \sum_{(i,l) \in C} t_{il} \quad (14)$$

The minimum project duration is achieved when the fastest implementation modes are chosen by all activities, and meanwhile, all sub-activities begin from the start point. Accordingly, a primary action plan is produced and its duration cannot be more decreased by increasing the productivity of activities. Then the control path of this program can be specified. According to the equation, if there is no backward controller in the control path, the resulting program is the best solution to the allocation of resource. Otherwise, additional reduce in project duration is achieved only by extending the duration of some of the backward control sections. This can lead to the production of new backward control components. By using a backward controller segment and identified prerequisites, the proposed problem can be simplified. This can be possible by performing all tasks without prerequisites fulfillment with the fastest

Power System Technology
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implementation mode and beginning all sub-activities at the first start time. Currently, the execution modes are considered as the only decision variables that meet the prerequisites of activities. Therefore, it is nice to know that how the prerequisites are described

Theorem 1. One of the following situations should occur to deals with a backward controller on ith activity.

a) The minimum time limit of SF or FF is existed between activities i and its previous activity, while a minimum time limit of SF is existed between activities i and its next activity.
b) The ith activity needs to ensure resource continuity constraints.

Proof:

If ith activity is permitted to stop. Because a backward controling segment is exsited on activity i and this activity is permitted to stop, the control path passes only one of the sub-activity of ith activity, and this is inactivity of a sub-activity of the backward controller. Without losing its generality, it can be assumed that this is a sub-activity of aij. Consistent with the definition of the backward controller, the previous control point must be recognized later than the next control point. At that time the control point of the previous activity must be the end point of aij and its successful control point must be the beginning point of aij. To meet this state, ith activity and its previous activity should have at least an SF or FF time limit. Also, ith activity and its next activity should consume at least an SF or SS time limit.

If there is no minimum SF or FF time limit between ith activity and its previous activity, or if there is no least SF or SS time limit between activity i and its next activity. At this moment, the previous control point of ith activity should be the beginning point of an aij sub-activity and the next control point of this activity should be the end point of an aij' sub-activity. Also, the beginning time of aij must be longer than the end time of aij'. These incomes that the two sub-activities cannot be the same sub-activity, and j> j' to ensure that the control path passes through unit j before than unit j', the resource connection limitation must be fully continued by ith activity

4. Problem solving methods

In this section, two evolutionary methods consist of NRGA and NSGA-II are introduced to solve the proposed problem. The following are the standard multi-objective indicators that are used in the analysis and comparison of obtained solutions.

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NSGA-II

Non-dominated sorting genetic algorithm is one of the most popular and commonly used optimization procedures in the field of multi-objective optimization [30]. This algorithm was introduced by Deb in 2002. In addition to all the performance of NSGA-II, it can be reflected as an outline for the creation of several multi-objective evolutionary approaches. This algorithm and its unrivaled methodology to multi-objective optimization problems have been applied repeatedly by different researchers to construct new-fangled multi-objective optimization algorithms. Absolutely, this algorithm is one of the most basic members of the collection of multi-objective evolutionary optimization algorithms, which can be named the second generation of such approaches. To explain the NSGAII method, three topics of sorting, determining the density of people in the search space and how to select particle to produce the next generation are stated respectively.

Non-dominated sorting

The problem of computational cost of MOEA methods such as NSGA, which was equal to O(mN3) for the N population and m utility functions, will be maximally equal to O(mN2) with this algorithm. It should be noted that this advantage is possible against the increase of storage space from O(N) to O(N2). If two characteristics ni and Si are calculated for each particle i, by calculation of these two characteristics the O(mN2) will be obtained. The important point is that ni reperesents the number of particles dominating i and Si is the set of dominated particles by i.

So, particles with ni=0 are the first Pareto front or F1. For each member of Fi, the set of dominated Si is considered and the nj corresponding to the jth member of it is reduced. Individuals in which nj=0 will belong to the set H. After completing H for all members of F1, we can say that H is the second Pareto front. To continue, set F1 aside and consider H as the first Pareto front. Therefore, the above process is repeated for the rest of the members. The concept of allocating different ranks to the solutions is seen in Figure 1.

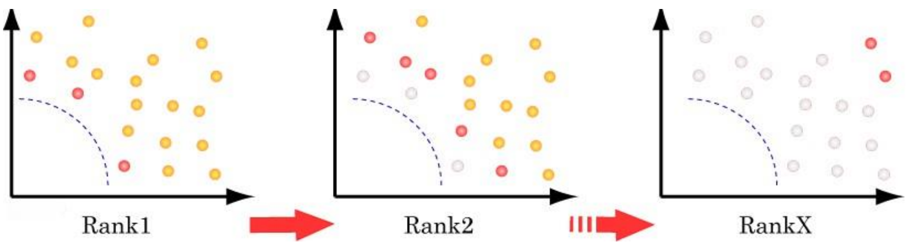

Figure 1. Allocating different ranks to the solutions in the NSGA-II method

Power System Technology
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Crowding distance

To determine the density of particle in a population around a certain point that will provide a criterion for regulating diversity in the population, the average of the closest particle on both sides of the mentioned point is considered for all utility functions. The quantity of idistance indicates the size of the largest cuboid, which includes, the mentioned particle and no other particles, which is entitled the crowding distance. Figure 2 shows this notion for two utility functions.

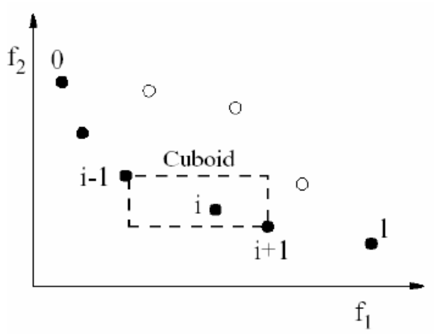

Figure 2. Calculation phase of crowding distance

Binary tournament selection operator

This selection operator makes it possible to reach the Pareto front in the last generation in a uniform and homogeneous way. However, even other MOEA algorithms, such as PAES, do not guarantee uniform access to all parts of the Pareto Front if they converge on the Pareto Front. In fact, when comparing two particles, a particle is selected who is related to the Pareto front is higher (better) or has a lower degree of dominance. If both individuals belong to the same Pareto front, ie have the same degree of dominance, a particle is selected who is less similar, ie in a less crowded environment or with a larger crowding distance. The first condition causes the population to converge towards the optimal points and the second condition causes the optimal points to be homogenized across the first Pareto front.

To execute the NSGA-II algorithm, the initial parent population P is first produced. The population is sorted according to the sorting algorithm and each particle is assigned a Pareto front rank. The problem of multi- objective optimization has now become a simple problem of minimization as a function of the Pareto front desirability. Binary tournament selection operators, crossover, and mutation are used to create a population of children (Q) with N children. From this generation on, the way of working will be different due to the application of the process of elitism. In the process of elitism, a combined population of parents and children is formed first. The hybrid population is then sorted based on the crowding distance operator, and its N better individual is considered as the next generation population Pt + 1.

Power System Technology
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Then, using the N population of Pt + 1 and using the operators of selection, crossover and mutation, the N population of Qt + 1 is constructed.

In this algorithm, population diversity in each generation will be ensured by applying the crowding distance operator when selecting a binary tournament in which no sharing parameter is required. Therefore, it will not have the weakness of other methods such as NSGA. Moreover, the crowding distance in the space of utility functions is calculated, which of also can be calculated with the space of parameters. Another point is that in constructing the population of each generation, the method of selecting a + b is used instead of (a, b), which will increase the stability of the method and will ensure that the good particles of the previous generation are not eliminated in the new generation. The implementation of the NSGA-II method is shown in Figure 3

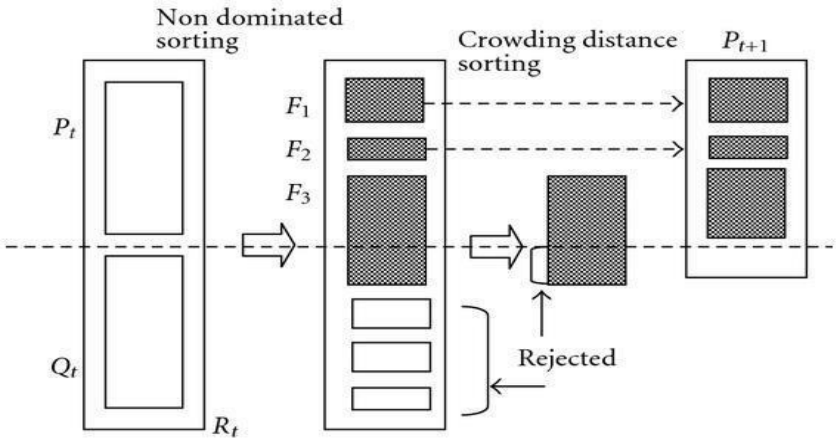

Figure 3. General procedure for implementing the NSGA-II method

NRGA

On the other hand, in 2008, a multi-objective evolutionary algorithm called genetics algorithm based on non-dominated ranking was successfully developed by Al Jadaan et al. [31] to optimize non-convex, nonlinear and discrete functions. Based on the problems in the previous approaches, they developed a new approach by combining a ranking-based roulette wheel selection operator with a Pareto-based population ranking algorithm. In most cases, this algorithm is able to achieve a better range of solutions at the Pareto boundary as well as earlier convergence to the optimal Pareto boundary, compared to other multi-objective evolutionary algorithms; but the main difference between NRGA and NSGAII algorithms is in the selection strategy. In the NRGA algorithm, we use a ranking-based roulette wheel operator instead of a crowding distance operator. This operator is designed in such a way that better members with

Power System Technology
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better fitness are more likely to be selected for reproduction and to form the next generation. The pseudocode of this algorithm is shown in Figure 4.

```
Initialize population P
  Generate random population with size N
  Evaluate objective values
  Assign rank (level) based on Pareto dominance
Generate child population Q
    Rank based on roulette wheel selection recombination and mutation
for i=1 to N_F do
    for each member of the combined population
    (P U Q) do
       Assign rank (level) based on Pareto – sort
       Generate sets of non – dominated fronts
       Calculate the crowding distance between members on each front
    end for
      (elitist) Select the member of the combined population based on the least dominated N solution
      to make the population of the next generation. Ties are resolved by taking the less crowding
      distance.
   Create next generation
     Rank based on roulette wheel selection recombination and mutation
End for
```

Figure 4. The pseudocode of NRGA

Multi-objective standard indicators

Now it is time to identify the multi-objective standard indicators. One of the ways to deal with these issues is to use performance measures indicators [32]. Some of these indicators are described below:

Number of Pareto Solutions (NPS)

This criterion is equal to the number of output solutions each time the algorithm is executed. In comparison between several algorithms, this criterion is defined as the number of output responses resulting from the

execution of each algorithm. Obviously, the more Pareto answers one method has, the more desirable that method is.

Mean Ideal Distance (MID)

This criterion is used to calculate the average distance of Pareto solutions from the origin of coordinates. In the following relation, it is clear that the lower this criterion, the higher the efficiency of the algorithm.

Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f1_i - f1_{best}}{f1_{total}^{max} - f1_{total}^{min}} \right)^2 + \left(\frac{f2_i - f2_{best}}{f2_{total}^{max} - f2_{total}^{min}} \right)^2}}{n} \quad (15)$$

$$SNS = \sqrt{\frac{\sum^{n} (MID - C)^2}{n-1}} \quad (16)$$

$$C = \sqrt{f1^2 + f2^2}$$

Computational time (CPU time)

In large problems, one of the most important criteria is their execution time, and therefore the execution time of the algorithm is considered as a quality evaluation criterion. It is clear that the lower this criterion, the higher the efficiency of the algorithm.

Maximum Dispersion Criterion (MS)

The maximum dispersion index is defined as following equation. It is clear that the higher this criterion, the higher the efficiency of the algorithm

Scattering of non-dominated solutions (SNS)

This index is presented to identify the scatter and variation of the obtained Pareto solutions. It is clear that the lower this criterion, the higher the efficiency of the algorithm.

5. Computational results

After stating the problem and explaining and mathematical modeling, in this section we will express the case study and the results. This section includes the problem under study, population size, probability of crossover and mutation, and comparison of algorithms and computational results that the contents of each item are presented in the relevant subsection.

Garbage collection problems that have consequences such as environmental pollution, political and social tensions and excessive costs for municipalities. Instead of converting waste into compost, national and provincial managers, including the municipality of “Sari”, have turned their attention to converting waste into energy (electricity), and in this regard, a contract has been signed for the construction of a waste incineration plant with a daily capacity of 450 tons. Sari is the provincial capital of Mazandaran province, located in the north of Iran, between the

Power System Technology
ISSN:1000-3673
Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

northern slopes of the Alborz Mountains and southern coast of the Caspian Sea. The most important advantages of waste incineration plant are low required area, independence from climatic conditions, speed and ease of waste disposal, clean usable ash, rapid reduction of waste volume, disposal of hazardous waste, reduction of maintenance and waste disposal costs, reduction the amount of air pollutants, and reduction in the risk of surface water pollution. According to the information obtained from the officials of this organization, the transportation of waste over a distance of more than 120 kilometers and the equivalent cost of more than 200 billion Rials per year was estimated. On the other hand, the type of contract in this power plant is BOT and the foreign investor is China. The mentioned project has been constructed in Mazandaran province, Sari city, 10 km of Khazarabad road, south of industrial town No. 1, on a land with an area of about 42,000 square meters. The general process of a waste incineration plant is as shown in Figure 5.

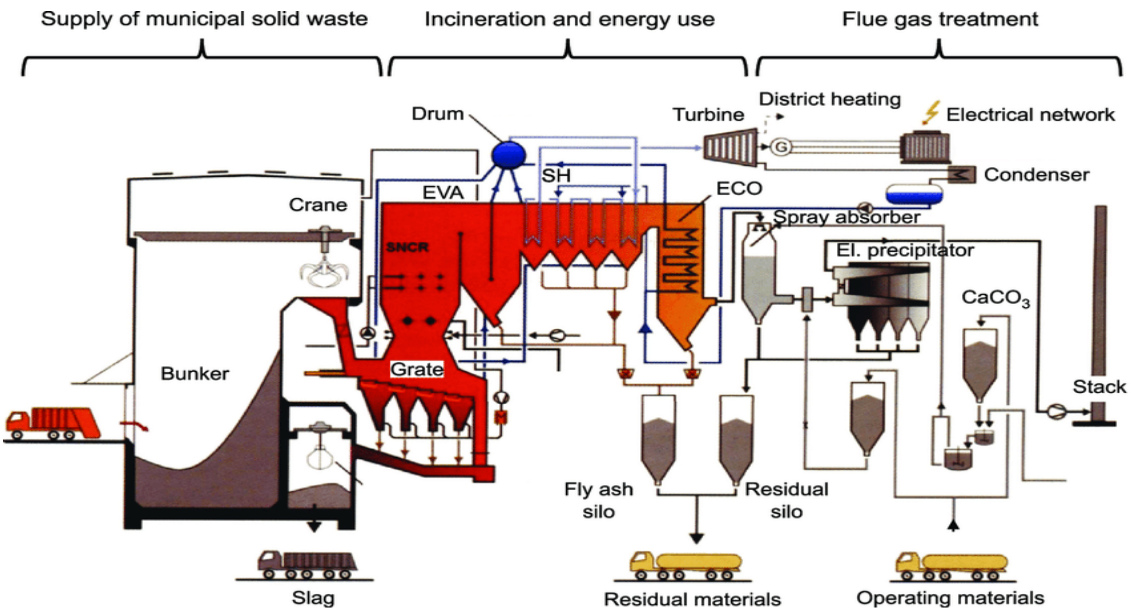

Figure 5. The general process of a waste incineration plant

Since the project is in the early stages of construction, this research can help to optimally allocate the physical, financial, and human resources of the project. On the other hand, we can also mention the improvement of activity schedule.

In this section, a small project of the whole waste incinerator project is first analyzed. The project consists of five units whose input data are presented in Table 2. Each unit contains 14 activities displayed in Figure 6. This is a routine project and therefore the amount of work of each activity in different units is always the same. The project manager needs activities 2, 4

Power System Technology
ISSN:1000-3673
Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

and 11 to be executed without break in order to save money. Now we have to compute the minimum project duration.

Activity	Unit of duration (months)		
	Mode 1	Mode 2	Mode 3
1	3	2	1
2	8	7	6
3	11	9	8
4	5	4	3
5	10	9	8
6	6	4	2
7	12	10	8
8	10	7	5
9	2	1	1
10	4	2	1
11	4	3	2
12	5	3	2
13	4	3	1
14	3	2	2

Table 2. Information on different scenarios and project schedule

Because activities 2, 4, 7, and 11 meet the preconditions that a department can be a backward controller, only the implementation types of these activities should be considered as decision variables. On the other hand, this research can help in the optimal allocation of physical, financial, and human resources of this project. For this purpose, the available resources and the required resources for each activity are presented in Table 3.

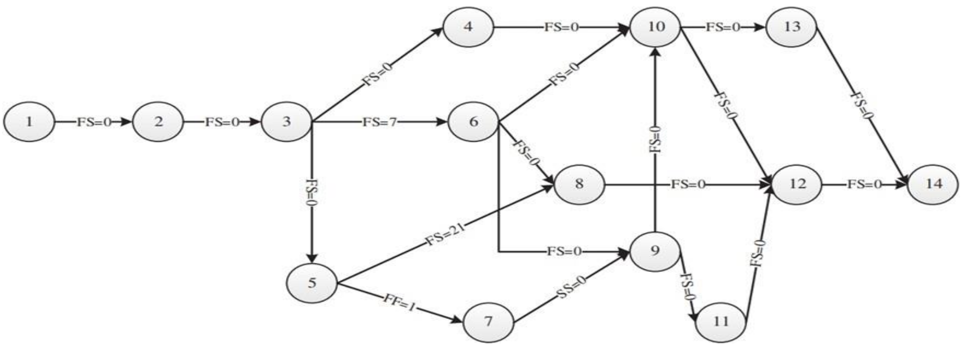

Figure 6. Activity on node (AON) diagram of the proposed project

Power System Technology
ISSN:1000-3673

Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

Activity	Resources required for each activity under different modes (Ki) per unit time								
	Physical (tone)			Financial (Million Toman)			Human (worker)		
	Mode 1	Mode 2	Mode 3	Mode 1	Mode 2	Mode 3	Mode 1	Mode 2	Mode 3
1	9	15	33	54	82	167	1	2	5
2	6	8	10	6	8	10	1	2	3
3	2	3	4	4	6	7	1	2	3
4	32	41	55	23	30	41	1	2	4
5	3	4	5	3	4	5	1	2	3
6	4	7	15	9	15	32	0.5	1	2.5
7	1.5	2	3	3	4	6	0.5	1	2
8	8	12	18	8	12	18	1	2	3
9	141	285	285	165	340	350	1	3	4
10	26	53	108	23	48	98	1	2	5
11	23	32	50	25	35	53	0.5	1	2
12	9	16	25	18	32	50	1	2	3.5
13	11	15	50	31	42	128	1	2	7
14	48	75	75	106	162	163	1	2	3
Source available	736 tones			2.1 billion Toman			50 workers		

Table 3. Information on required resources and available resources for allocation

To further comparison of different methods, this section provides a more complete examination using the subsequent random test examples. These tests are executed on a personal computer with a 2.00 GHz processor. All tested algorithms are coded with MATLAB software and verified under Windows 10. Since there are no accessible test samples for resource allocation issues in building projects (due to security issues by operating organizations), we randomly create test samples with the subsequent steps:

Step 1. Randomly define the scale of the problem, indicated by A(I) U(J), so that I and J represent the quantity of activities and units, individually.

Step 2. Create a set of problem sizes for each activity randomly. Define the kind and extent of the minimum time limit between activities i and each of its subsequent activities. Then randomly define whether the resource connection limit for each activity i should be met.

Step 3. Randomly select a positive integer Ki to indicate the number of alternative execution modes of activity i. Then the unit of duration of activity i in mode k, or dijk, is allocated a random integer among [1- 10]. Reminder that the unit of duration of activity in both cases can not have the same value.

Step 4. Randomly determine the resources available and required for each activity. Thus, human resources are assigned a random integer among [1-100], physical resources are assigned

Power System Technology
ISSN:1000-3673

Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

a random integer among [3- 60], and financial resources are assigned a random integer among [50-180].

Experimental design

In the late 1940s, Taguchi presented novel statistical notions and later proved to be valued implements in quality control and improvement, and since then, many Japanese artisans have applied this method to develop products and quality. They use the process [33]. Taguchi combined and formed singular groups of orthogonal arrays (OA) to show his investigates. Orthogonal arrays assist the design procedure of investigates. The design of an experiment includes choosing the most suitable orthogonal array, defining the aspects with the proper columns, and finally the location of the experiments (test situations). In this study, we use the smaller is better equation of the Taguchi method as the following relation.

$$SN_S = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (18)$$

Since the mathematical model of this research has two objective functions, an equation using standard multi-objective indices is used as the response in Taguchi method; this relationship is as follows.

$$MCOV = \frac{MID}{MS} \quad (19)$$

As explained, the Taguchi method reduces the parameter setting time by reducing the number of experiments. First, the parameters that we want to set in each algorithm are specified. To do this, related articles were studied and candidate levels were identified among them, which is shown in Table 4.

Algorithms	Parameter	Parameter levels		
		Level 1	Level 2	Level 3
NSGA-II	Pc	0.7	0.8	0.9
	Pm	0.05	0.10	0.15
	N-pop	50	100	150
	Max-iteration	200	300	400
NRGA	Pc	0.7	0.8	0.9
	Pm	0.05	0.10	0.15
	N-pop	50	100	150
	Max-iteration	200	300	400

Table 4. Different levels for the parameters of each algorithm

Using Minitab software, levels of parameters and arrays of orthogonal are obtained for experiments, and after determining the number of experiments for each algorithm, the

Power System Technology
ISSN:1000-3673
Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

algorithms are tested with the same specific levels and run thirty times, and the results obtained from these tests are averaged, then they are

weightless, the S/N graphs are obtained. Finally, L9 orthogonal arrays were selected for NSGA-II and NRGA algorithms using minitab software. After performing the algorithms for each of the above experiments, response values were obtained for the Taguchi method. These orthogonal values and arrays are presented in Table 5.

Experiment	Selected levels of parameters				Response	
	Pc	Pm	N-pop	Max-iteration	NRGA	NSGA-II
1	1	1	1	1	6.4234e-006	4.497e-006
2	1	2	2	2	9.5085e-006	9.3753e-006
3	1	3	3	3	6.7366e-006	3.857e-006
4	2	1	2	3	4.3413e-006	7.0235e-006
5	2	2	3	1	5.3981e-006	9.5885e-006
6	2	3	1	2	9.4061e-006	1.594e-005
7	3	1	3	2	5.9087e-006	3.8218e-006
8	3	2	1	3	5.5662e-006	4.3919e-006
9	3	3	2	1	7.6662e-006	1.417e-005

Table 5. The L9 orthogonal array and computational results for NSGA-II and NRGA

Finally, after drawing the signal-noise diagrams of each algorithm, the best values of the parameters can be identified. These values are shown in Figures 7 and 8.

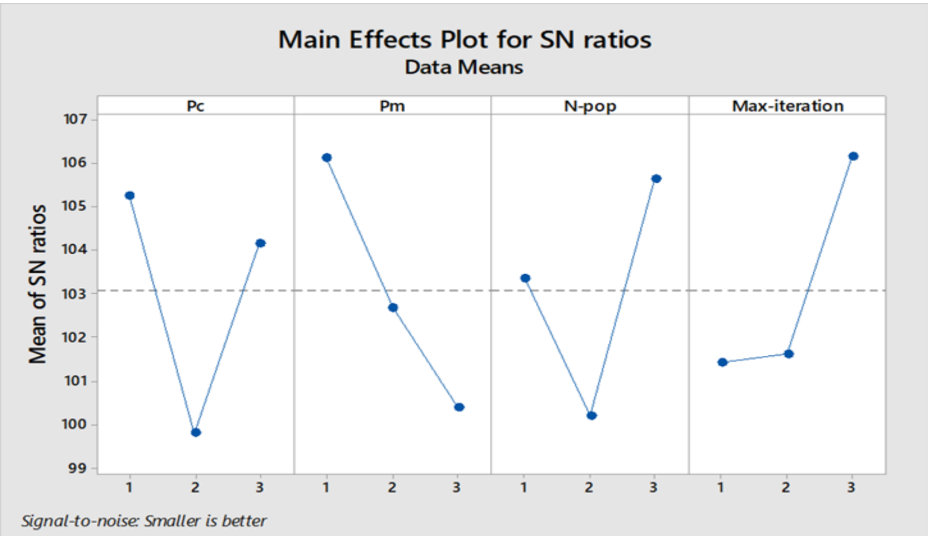

Figure 7. NSGA-II algorithm's signal-noise diagram

Power System Technology
ISSN:1000-3673
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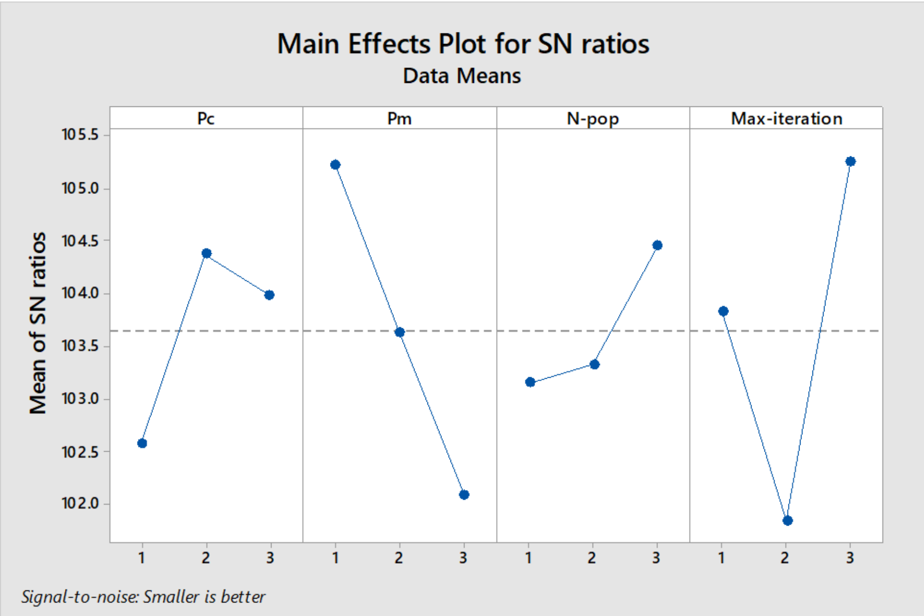

Figure 8. NRGA algorithm's signal-noise diagram

Finally, the proposed bi-objectives model can be solved using tuned algorithms. After designing the experiment and setting the parameters, the appropriate parameters in each algorithm are now specified and it is time for the algorithms to be implemented and compared with the generated problems. After solving the proposed mathematical model using the mentioned methods, finally Table 6 shows the results for the problem.

Problem	NPS↑		CPU time↓		MID↓		MS↑		SNS↓	
	NSGAII	NRGA	NSGAII	NRGA	NSGAII	NRGA	NSGAII	NRGA	NSGAII	NRGA
1	12	11	52.88	60.36	0.8814	0.8333	91360643	62138780	78662305	80690831
2	10	10	115.67	129.45	0. 9326	0.9236	92365996	72365261	81253626	85985652
3	14	12	199.81	220.89	0. 8962	0.8985	94105562	86235232	86523568	89633586
4	13	10	302.70	425.85	0. 7963	0.7920	98623571	93526874	94303203	95235874
5	11	9	706.28	835.94	0. 9036	0.8687	106752362	102365994	99320378	102578963
6	11	12	989.72	1172.32	0. 7896	0.8952	113569854	108569266	112536265	120235668

Table 6. Computational results of algorithms for six sub-problems

Power System Technology
ISSN:1000-3673

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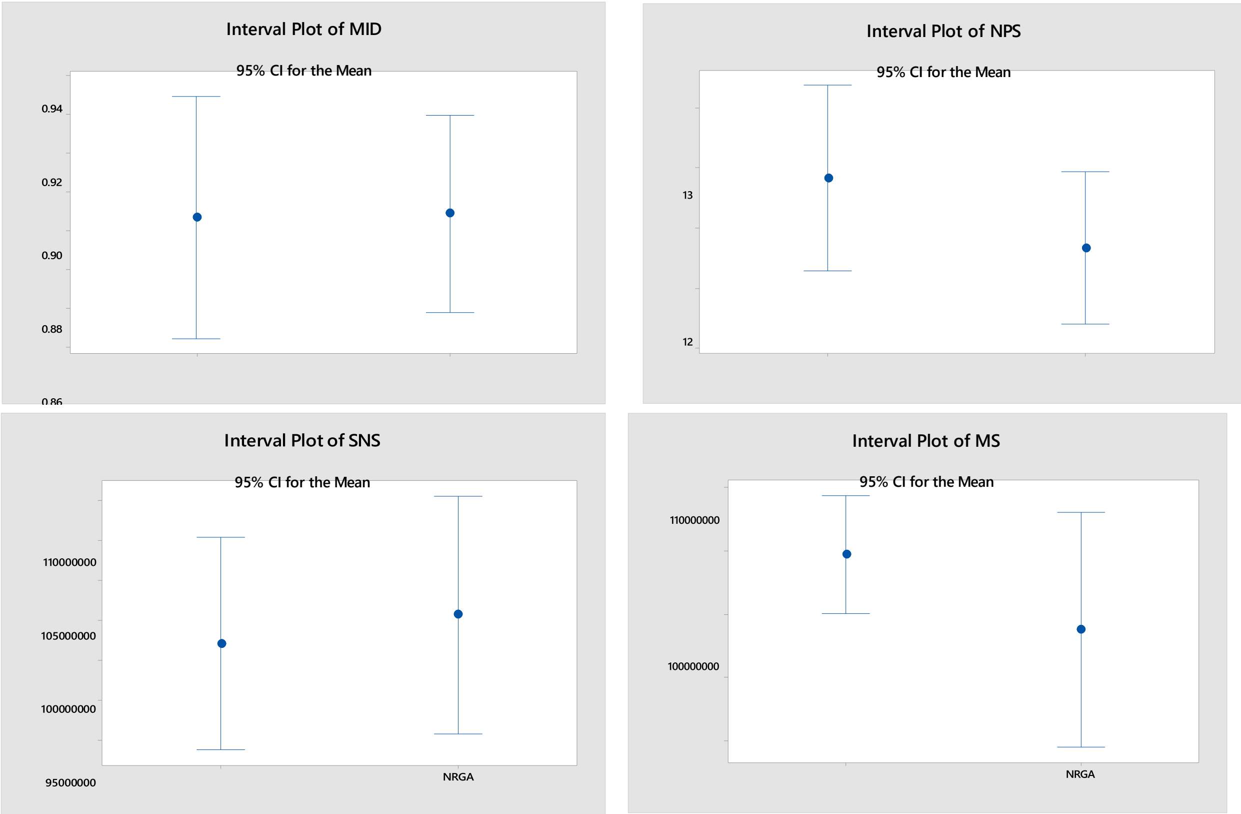

Figure 9. Statistical analysis according to standard indicators

As can be seen, the NSGA-II algorithm performs better in terms of NPS index, but the NRGA algorithms perform better in terms of MID index. NSGA-II algorithms also have the best performance in terms of MS and SNS indicators. In addition, in terms of CPU time index, the algorithms are compared in Figure 10, which, as it turns out, the NSGA-II algorithm performed best. Also, for a better understanding of a Pareto diagram of the first problem (case study) is presented in Figure 11.

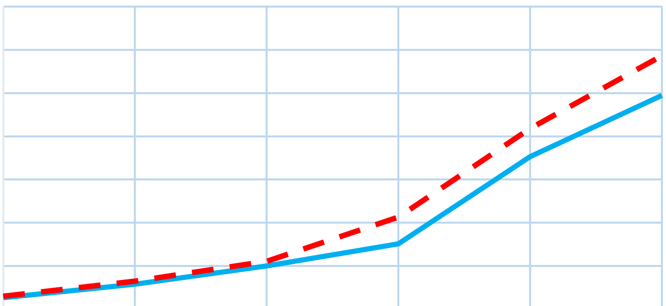

Figure 10. Comparison of algorithms by CPU time index

Power System Technology
ISSN:1000-3673
Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

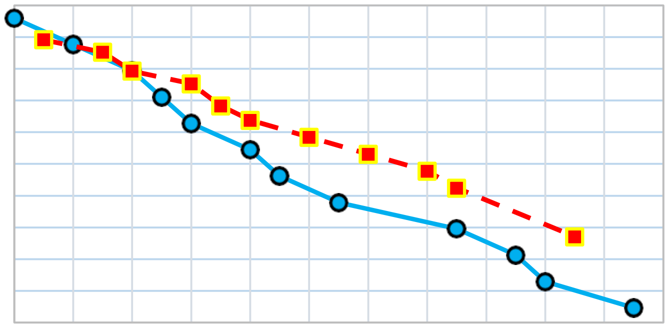

Figure 11. Pareto diagram for the first problem (case study)

Given that in this case we have five standard indicators including: NPS, MS, SNS, MID and CPU time and also two algorithms including NSGA-II and NRGA are available, it is easy to identify the best algorithm according to the results. Because NSGA-II algorithm in four indicators of NPS, MS, SNS and CPU time has shown better performance than NRGA, so this algorithm is selected as a more efficient algorithm. Therefore, according to the experts in this field, information related to one of Pareto solution is provided. According to experts, the seventh Pareto solution of NSGA-II algorithm was selected as the appropriate solution and this point is marked in Figure 12 with a rhombic shape and red color. It should be noted that the values of the first and second objective functions for this solution are equal to 1409 and 1705001286, respectively.

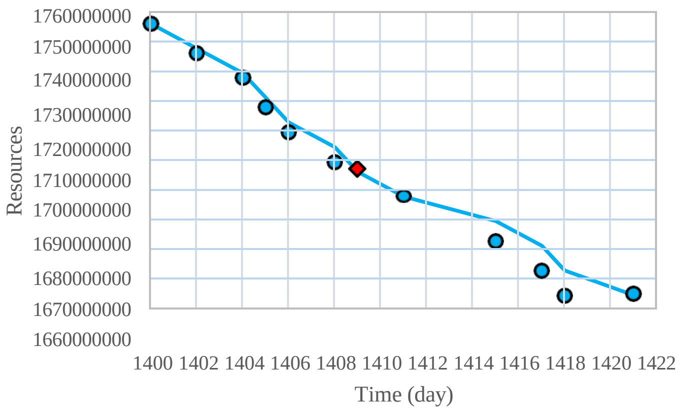

Figure 12. The seventh selected solution from the NSGA-II Pareto front

Table 7 also shows that values xik for each activity is selected in which mode, with values 1 representing the selected mode. For example, the first activity will occur with mode 1. In

Power System Technology
ISSN:1000-3673
Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

addition, as mentioned above, the construction project is carried out under selected conditions in 1409 days, which is 9 days more than.

the optimal time (problem solving with only the first objective function). On the other hand, the total consumption resources for 1409 days of the project length from three types of physical, financial and human resources is equal to 1705001286 units, the values used of each source are presented in Figure 13.

Activity	Mode 1	Mode 2	Mode 3
1	1	0	0
2	0	1	0
3	1	0	0
4	0	0	1
5	0	1	0
6	0	1	0
7	1	0	0
8	0	0	1
9	0	0	1
10	0	1	0
11	0	0	1
12	0	1	0
13	1	0	0
14	0	0	1

Table 7. The value of xik for the selected solution

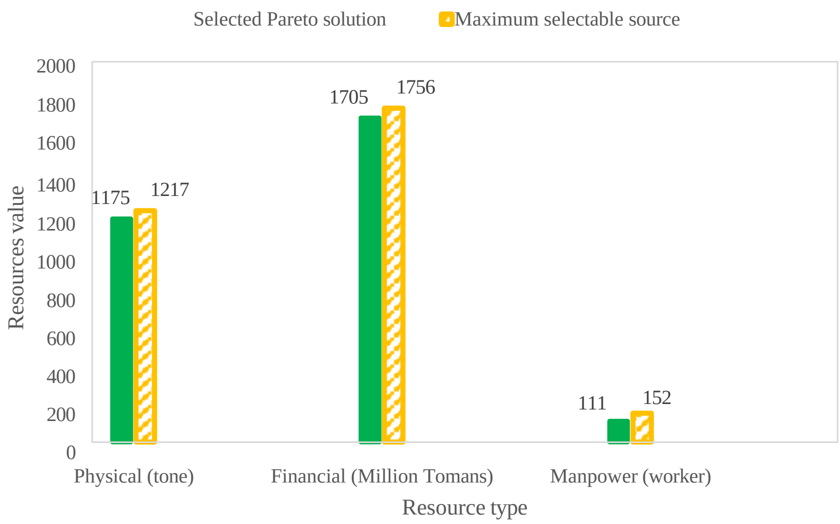

Figure 13. Total values of resources used versus maximum usable resources

Power System Technology
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Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

As shown in Figure 13, 111 manpower has been employed to complete the project, and if the project was compressed, this number could reach a maximum of 152 workers. On the other hand, 1.705 billion tomans of budget was used from the maximum budget (1.756 billion tomans). Also 1175 tons of physical resources were used, with a maximum of 1217 tons of physical resources available.

Addressing the resource allocation issue in construction projects with the aim of minimizing project duration and defining the optimal modes of implementation and start time for all sub-activities, taking into account priority relationships, logical relationships and coherence in resource allocation, is the existing challenge of experts in this field. Solving this type of problem is one of the problems in construction projects, because resource continuity constraints and different kinds of time restrictions should be reflected in the optimization procedure. Therefore, this research introduces a new bi-objective model for optimal allocation of resources to construction project activities and simultaneously examines the effective factors including time and cost on this model. The purpose of this suggested model is to minimize project completion time, while also minimizing various resource consumption. Therefore, we are looking for a balance between time and allocated resources to be desirable for the relevant development organizations. To solve the proposed bi-objective model, some multi-objective evolutionary algorithms including NSGA- II and NRGA are used. At first, the parameters of these algorithms are calibrated by Taguchi method and finally they are utilized to solve the model. In order to quantify the parameters of the proposed model, a case study related to the waste incineration plant in Iran was presented and for further comparisons, several numerical examples in larger dimensions were used. These algorithms were compared by several standard multi-objective criteria common in this field and the results were analyzed by statistical methods. Finally, the results showed the superior performance of the NSGA-II algorithm. The results of this algorithm were explained for a selected Pareto solution according to experts. Since every research is done in a specific time and place, so it has certain limitations that users of the research results need to use them more carefully and cautiously. One of the most important limitations of the present study is the following:

The present study in terms of location has been done only in the cities of one province, which may be the province under study and has its own conditions, and therefore in generalizing the results to other cities and departments, this issue should be considered.

- Lack of coherent research in this field and lack of backgrounds that can be designed and used in Iran.
- Lack of structural and systematic research in this field in the country and Mazandaran province
- It seems that more research can be provided by expanding and expanding this research, which includes the following:
- Modification and implementation of this model in other and similar construction projects

Power System Technology
ISSN:1000-3673
Received: 06-04-2024 Revised: 15-05-2024 Accepted: 28-06-2024

- Combining the proposed mathematical model with multi-criteria decision-making methods
- Using other meta-heuristic algorithms and exact methods
- Consideration of environmental considerations or aspects of sustainability
- Considering uncertainty in model parameters such as fuzzy, stochastic, and robust models

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