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HYBRID MULTI-POPULATION GENETIC ALGORITHM FOR MULTI CRITERIA PROJECT SELECTION

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Abstract. Resources scarcity, available capabilities and cost-benefit point of view, make it essential to select the best project(s) from available projects. Project selection process has a significant role in the success of investment. The main question is "what projects should be financed?" Applied approach to answer this, should be real, fast, global, flexible, economic and easy to use. It is clear that choosing a good approach for project selection problem with economic and non-economic criteria can be vital for a project manager to success within constraints. The complexity of the problem increases when the number of projects and the number of objectives increase. Therefore, in this research we aim to present a new heuristic method based on genetic and simulates annealing to select and rank available projects based on economic and non-economic criteria. Presented method starts from initial solutions including multi population generated solutions, and moves toward the final solution based on genetic operators and objective function. The proposed algorithm is evaluated on a set of randomly generated test problems with varying complexity. Comparison studies between our method with other recently method in the literature demonstrates the capability of it to find a good basket of projects. Experimental results prove that this method is applicable for all kinds of projects basket.

Keywords: Project Selection, Genetic Algorithm, Multi Criteria, Genetic Operators, Meta-Heuristic.
2020 MSC: 68W50.

1. Introduction

We always are facing choice in our life. Select the best ones between several choices by rank them based on data gathering and available constraints. A project manager also must select one or more projects from available portfolio based on his/her team capabilities, project benefit, vision, foresight and other criteria. In project selection process, general steps are gathering date, extracting decision criteria and rank all available projects to select the best ones based on our knowledge. The project selection process is a multi-criteria decision making (MCDM) problem. Several criteria have various importance

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based on manager's viewpoint. The complexity of this problem increases as the number of projects in portfolio and the number of criteria is increase. In the real world this field of study called as NP-hard problem based on its complexity (Nikkhahnasab and Najaf, 2013, Panadero, 2018) [12, 15].

Most of the real-world optimization problems and many academic popular problems are NP-hard. Project selection besides Routing and covering problems, Sequencing and scheduling problems, Knapsack and packing/cutting problems and Assignment and location problems are some cases of NP-hard problems (El-Ghazali Talbi, 2009, Nikkhahnasab and Najaf, 2013) [6, 12]. For NP-hard problems provably efficient algorithms do not exist and therefore meta-heuristics in pure and hybrid structure have wide applications to solve this kind of problems.

A meta-heuristic is described as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information to find efficiently near-optimal solutions (Osman and Laporte, 1996) [14]. Based on our knowledge and experience, genetic algorithm generally used to generate high-quality solutions to optimization and search problems. Project selection is an optimization problem and has a wide search space when the project portfolio is huge. Based on recent researches (Mohagheghi, et al. 2019) [11] genetic algorithm by relying on biological inspired operators such as mutation, crossover and selection can be effective in this field of study. In this paper, at first we formulate our problem as a mathematical model and then develop a new meta-heuristic based on genetic algorithm and simulated annealing to solve project selection problem. Proposed method is a multi-population based and called new hybrid multi-population genetic algorithm (NGA). In NGA at first, a pool of feasible initial solutions is generated and all solutions are divided in some groups. The best solution in each group called commander and each commander competes against others (new generated solutions or other commanders) to be final solution. Result of each competition is determined by probabilistic rules based on simulated annealing to check all search spaces as much as possible. We use some heuristic mutation and crossover in NGA. Compared to basic genetic, NGA check more search spaces and yield more competitions between capable solutions, because of multi pupation technique and probabilistic rules. Therefore the contributions of the proposed model are:

- Development of a mathematical model for project selection problem based on proposed situation and multi criteria approach.
- Development of a new multi population genetic algorithm (NGA) based on lion's life (we will explain later).
- Using heuristic mutation and heuristic cross over.
- Hybridization of NGA with simulated annealing to check all search spaces as

much as possible.
The rest of paper is organized as follows: Section 2 presents the literature review of the project selection problem. The NGA is defined in Section 3. Section 4 devotes to verification and comparison study and finally Section 5 concludes the research.

2. Literature review

The following is an example of a theorem, proof, corollary, proposition and remark. In project selection methods, qualitative and quantitative criteria are taken into account to projects ranking (Nowak, 2013) [13]. In the real world, there are many criteria affected to selection process. Therefore, this problem in real size can be categorized in NP-hard and using heuristic and meta-heuristic approach can be effective to solve them. During recent decades many researchers have attended project selection by developing various heuristics and meta-heuristics. Carazo et al. (2010) [4] presented a multi-objective model for portfolio project selection with the set of objectives pursued by the organization, regarding the optimum time to launch each project within the portfolio without the need for a priori information on the decision-maker's preferences. They solved the problem by a meta-heuristic procedure based on Scatter Search. Nikkhahnasaba and Najafi (2013) [12] considered the net present value of the project portfolio as an objective function and used a genetic algorithm to solve the problem. Nowak (2013) [13] developed a method based on interactive approach. He assumed a single portfolio is proposed to the decision maker in each iteration. Fernandez et al. (2015) [8] an Ant Colony Optimization to solve multi-objective project portfolio optimization problem. They considered a fuzzy outranking preference model to solve the problem. Esfahani et al. (2016) [7] presented a new definition and formulation of modern portfolio theory (MPT) and finally developed a search heuristic to solve the project selection problem. Brester et al. (2017) [3] considered project selection portfolio problem as a knapsack constrained multi-objective optimization problem and used island meta-heuristic to solve it. Kimar et al. (2018) [9] considered expected benefit of portfolio as an objective function and introduced one meta-heuristic based on Teaching-learning-based optimization (TLBO) a tabu search (TB) to optimize selection and scheduling of projects. Panadero et al. (2018) [15] developed a simulation-optimization algorithm based on variable neighborhood search and monte carlo simulation. They considered expected net present value as an objective function. Tofighian et al. (2018) [16] considered multi-objective project selection problem and modeled it based on net profit. They also present a meta-heuristic based on genetic algorithm to solve the problem. Davoudabadi et al. (2019) [5] proposed a novel multi-criteria decision-making model using linear assignment approaches with interval-valued intuitionistic fuzzy sets (IVIFSs) for project selection problem. Kumar et al. (2019) [10] proposed a modified genetic algorithm to solve the real life project selection problems. The proposed algorithm was evaluated on a set of randomly generated test problems with varying complexity. The performance of the proposed GA was compared with TS algorithm and the results show that proposed GA outperforms the TS algorithm. Afshar et al. (2021) [1] proposed a model for selecting subcontractors and assigning available tasks in the project to them in order to reduce the costs of the GC. In their research a genetic algorithm is proposed to solve a real problem. For deep review in this area we refer readers to research done by mohaghehgi et al. (2019) [11]. They reviewed more than 140 papers on project portfolio selection area. Based on their research, selection of good project portfolio in short time and with good return is a main concern of each manager. Therefore, solution time and solution quality are main criteria in this regard. Considering a comprehensive problem based on the real world in project selecting area and development a good approach to solve the problem in good quality and reasonable time is a major gap in the literature. To yield this goal, in this research we are going to model th project selection problem and develop one population-based meta-heuristic for project selection. Computation time and solution quality are out main considerations to reach an effective meta-heuristic method. Based on Blum and Andrea (2003) [2], meta-heuristics have some basic properties as follows:

- Meta-heuristics are strategies that "guide" the search process.
- The goal is to efficiently explore the search space to find near optimal solutions.
- Techniques which constitute meta-heuristic algorithms range from simple local search rules to complex learning processes.
- Meta-heuristic algorithms are approximate and usually non-deterministic.
- They may incorporate mechanisms to avoid getting trapped in confined areas of the search space.
- The basic concepts of meta-heuristics let an abstract level description.
- Meta-heuristics are not problem specific.
- Meta-heuristics may make use of domain-specific knowledge in the form of heuristics that are controlled by the upper level strategy.
- Today's more advanced meta-heuristics use search experience (embodied in some form of memory) to guide the search.

Two main categories of meta-heuristics are:
1) Trajectory methods like basic local search, simulated annealing, tabu search and variable neighborhood search.
2) Population based methods like genetic algorithm, ant colony optimization and particle swarm optimization. Meta-heuristics in both trajectory and population categories, are good choice to solve the NP-hard problems like project selection in the real world. Proposed meta-heuristic is adaptable to above properties.

3. Mathematical Mode

One novelty of our research is develop a mathematical model for project selection problem. In this field of study most important criteria to select one or more projects among available ones are return of investment, credit and risk or project. Therefore our objective function is constructed by them. To model our problem, at first we need to define parameters. Table 1 describes all parameters.

TABLE 1. Description of parameters for mathematical model

or_i	optimistic return of project i
mr_i	most likely return of project i
pr_i	pessimistic return of project i
cr_i	estimated credit earned by doing project i
tr_i	estimated technical risk of project i (based on our team's knowledge in project scope)
fr_i	estimated financial risk of project i (based on our knowledge about employer)
c_i	cost of performing project i
w_i	importance of all kinds of risks (here i=1 and 2)
B	total in-hand budget
N_{max}, N_{min}	maximum and minimum number of projects that must be invested respectively (diversity constraint).
R_{min}	minimum expectable return (based on investor and also inflation rate)
V_{max}	maximum acceptable risk (based on risk taking of an investor)
n	number of projects
I_i	binary decision variable represents investigation in project i

We define:

$$r_i := \frac{or_i + 4 \times mr_i + pr_i}{6} \tag{1}$$

$$I_i := \begin{cases} 1 & if\ \ project\ i\ is\ selected \\ 0 & if\ project\ i\ is\ not\ selected \end{cases} \qquad i = 1,\ 2,\ \ldots,\ n \tag{2}$$

Now we present mathematical model as follow:

$$maxR = \sum_{i=1}^{n} r_i \times I_i \tag{3}$$

$$\max Cr = \sum_{i=1}^{n} cr_i \times I_i \tag{4}$$

$$minV = \sum_{i=1}^{n} (w_1 \times tr_i + w_2 \times fr_i) \tag{5}$$

Subject to:

$$\sum_{i=1}^{n} c_i \leq B \tag{6}$$

$$R \geq R_{min} \tag{7}$$

$$V \leq V_{max} \tag{8}$$

$$N_{min} \leq \sum_{i=1}^{n} I_i \leq N_{max} \tag{9}$$

$$w_1 + w_2 = 1 \tag{10}$$

Equation 1 calculates expected average of return in project i. Equation 2 represents a binary variable. Return, credit and risk are most important issues in all field of studies therefore equations 3, 4 and 5 are objective functions. Equation 3 and 4 maximum overall return and credit and also because that investors are risk averse equation 5 minimum overall risk of investment. If an investor does not care about the risk and just think about return the equation 4 can be eliminated (for risk takers). Equation 6 is about budget constraint and equations 7 and 8 say that return on investment and it is risk on project portfolio has minimum and maximum limit based on investor's viewpoint. Equation 9 restricts the number of project that can be selected and equation 10 is clear.

4. **The New Genetic Algorithm**

Presented meta-heuristic is based on lion's life. Unlike other cats, lions live in groups, called pride. One pride consists one male as a commander, up to three males, related females, and their cubs. The size of pride depends on available food and water. Fewer resources result smaller pride. Commander is the strongest lion within the pride and is responsible for guarding their territory and their cubs. He plays this role till another strong male defeat him and gain his pride. Female lions are the primary hunters of the group.

Male cubs must leave the pride in around two years old. They form small groups until they are strong enough to challenge male lions of other pride.

This kind of treatment, stimulates us to develop one approach called new multi-population genetic that hybridized with simulated annealing (NGA), to solve project selection problems. First of all, NGA needs an initial population of solutions therefore it is population based one. Care must be taken into account that all solutions should pass all constraints.

To generate each member of initial population, the following steps are considered:

Set I_i=0 for i=1,2,. . . ,n.

Used random integer generator to earn k (integer between N$_{min}$ and N$_{max}$)

For i=1: k

Used random integer generator to earn j (integer between 1 and n)

If $I_j > 0$ replace j with the nearest j (between 1 and n) that $I_j = 0$

Endif

If $\sum_{z=1}^{n} c_z \leq B - c_j$

$I_j = 1$

Endif

End for

Extract all I_i i=1,2,. . . ,n.

After that, all earned solutions are divided into some groups (prides). Solutions of each group must be more than 2. The best solution of each group is one that has more fitness function based on the weighted arithmetic mean of 3 objective functions as follows:

$$Fitness\ Function_k\,(FF_k) = e_1 \times R + e_2 \times CR - e_3 \times V \qquad (11)$$

e_j (j=1,2 and 3) is calculated by the investor viewpoint. Solution with the best FF in each group called commander. At next steps, new solutions (offspring) are generated by using heuristic mutation operation or order crossover operation in each group.

We use heuristic mutation and order crossover operations like ones done by Mirabi (2014). Figures 1 and 2 describe these operations. Care must to be account that order crossover operator can only be used for solutions with the same size (same number of projects that are selected for investment). Numbers in each chromosome indicate the number related to selected project.

			Selected substring			
	Parent 1	1	8	12	4	22
	Parent 2	18	5	4	2	13
Offspring 1		1	5	4	2	22

Fig. 1. The order crossover operator

		Select three genes randomly 1,12 and 22				
	Parent	1	8	12	4	22
Offspring 1		2	8	10	4	1
Offspring 2		3	8	15	4	2
Offspring 3		7	8	5	4	14
Offspring 4		13	8	9	4	2
Offspring 5		10	8	23	4	1
Offspring 1		11	8	1	4	5

Fig. 2. The heuristic mutation operator

Each new solution in each group, challenges all commanders and if defeats one of them (is better than it), becomes the new commander of the related group and previous commander and some worst solutions in the group are eliminated.

Let us use the following notations for our algorithm:

m: number of all initial solutions (all population of lions). m must be more than 4 because we need at least two groups with size of at least 2.

n: number of groups (prides). Each group has at least two solutions and therefore $2 \leq n \leq [m/2]$.

k: number of iterations that we need to generate new solutions in each group that challenge other commanders to replacement.

The pseudo code of NGA is as follows:

Input m, n and k

Describe fitness function (objective function)

Generated m initial solutions by random

Generate n pride numbered 1 to n

For j=1:$[m/n]$+1

For i=1:n

If there are unallocated solution,

Select one solution by random and allocate it to pride numbered i

End if

End for

End for

For i=1:n

Select the best solution in pride i based on the fitness function and called it as commander (commander = arg max (fitness))

End for

For i=1:k

For j=1:n

Generate some new solutions in pride j randomly by heuristic mutation of commander or order crossover between commander and one member of pride.

If new solution passes all constraints, compare it with all commanders based on FF. If new solution is better than one of them (based on fitness function)

called it new commander and replace it with the worst solution in the pride. Otherwise if it is better than worst solution of its group, replace it with the probability of $e^{-\frac{1}{FF_{new}-FF_{worst}}}$ (based on simulated annealing or SA)
End for
End for
Compare all commanders and select the best for the final solution. In brief, NGA can be illustrated as a flowchart shown in figure 3.

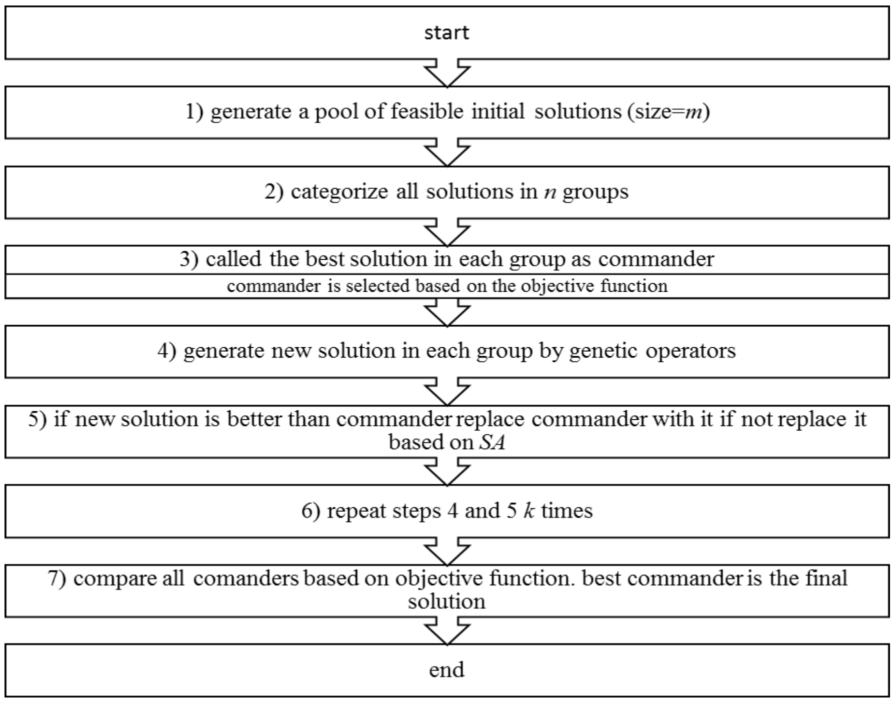

Figure 3. Brief illustration of NGA

5. **Comparison Study**

In this section, a computational study is carried out to compare the NGA with the best developed heuristics in project selection area. The following methods are selected from the literature:

Variable neighborhood search (VNS) developed by Panadero et al. (2018).

A hybrid TLBO-TS algorithm (HTT) developed by Kumar et al. (2018).

We consider 100 construction projects from 17 consulting company in Yazd city. Optimistic, most likely and pessimistic returns of each project are estimated based on comment of CEO of related company. We have the same approach about the credit and technical risk and financial risk of each project. B is set to 5×10^{11} and we also set N_{max} to 50, 70, 80 and 100 and N_{min} to 5, 10, 20 and 30. R_{min} and V_{max} are considered 0.22 and 0.40, respectively.

Finally, $w_1=w_2=0.5$. *PM* index was used to compare all methods as equation 12.

$$PM = \frac{Heu_{sol} - Best_{sol}}{Best_{sol}}, \qquad (12)$$

where the fitness function (FF) obtained by a given algorithm is Heu_{sol} and Best_{sol} is the best OF obtained by all algorithms. The programs are coded in MATLAB. Standard approach in the experimental comparison of evolutionary algorithms is to repeat several runs on the same problem because of stochastic nature of the algorithms. For equal condition between three methods all algorithms are run 10 independent times with a stopping criterion based on a finite number of iteration. Considering all configurations tested, we obtain a total of 16 class of problem and 160 problem instances.

m set to 80 for NGA and termination condition set to 20 seconds or 1000 repetition (k) for all methods (each happened earlier).

In Table 2, Min, Max and the average PM of each method is shown. Also, the average time to solve 10 instances are given for each method. The columns labelled "Min" show, in subscript, the number of instances for which the algorithm solution was equal to the corresponding Best_{sol}. For example, consider the second row of Table 2. NGA, VNS and HTT yielded the Best_{sol} six times, four times and once, respectively. Ave rage time of solution for NGA, VNS and HTT are 1.19 seconds, 1.81 seconds, and 2.75 seconds, respectively. As shown in Table 2, New Genetic Algorithm (NGA) out performs others based on PM value. VNS yields good quality but is not fast enough and HTT is almost fast but is not accurate enough.

At this stage the ANOVA test can be applied to show whether the results gained by all methods are statistically similar or not. The ANOVA procedure tests these hypotheses:
H0: $\mu 1 = \mu 2 = \mu 3 = \mu 4$, all results are the same
H1: two or more results are different from the others

With the $\alpha = 0.05$ significance level, computations are shown in Table 3.
In Table 3, VR=9.2>F=2. 7, therefore the results in Table 2 are not the same and differences are statistically significant. Also, Table 2 demonstrates that NGA and VNS are more competitor. For detail comparison between NGA and VNS, we should check that the differences between solutions of two algorithm are statistically significant or not. For this, the hypothesis that the population corresponding to the differences has mean (μ) zero can be tested; specifically, test the (null) hypothesis $\mu = 0$ against the alternative$\mu > 0$. This test is performed like what done by Mirabi (2014) between two best methods based on Table 2 (NGA and VNS). It is assumed that the differences between solutions (FF) is a Normal variable, and choose the significance level $\alpha = 0.05$. If the hypothesis is true, the random variable $T = (\overline{X}_1 - \overline{X}_2)/\sqrt{(S_1^2/n_1) + (S_2^2/n_2)}$ has a t distribution with:

Table 2. PM values for comparison studies between all algorithms (times are in second)

Class of problem	$Nmax$	N_{min}	NGA				VNS				HTT			
			Min PM	Average		Max PM	Min PM	Average		Max PM	Min PM	Average		Max PM
				PM	Time			PM	Time			PM	Time	
1	50	5	0_6	0.04	1.07	0.13	0_5	0.01	1.82	0.03	0_2	0.16	1.96	0.19
2	50	10	0_6	0.05	1.19	0.10	0_4	0.05	1.81	0.14	0_1	0.12	2.75	0.16
3	50	20	0_5	0.07	2.38	0.11	0_5	0.01	2.71	0.09	0.02	0.06	5.40	0.21
4	50	30	0_6	0.04	5.26	0.09	0_3	0.02	4.07	0.05	0_1	0.06	8.40	0.13
5	70	5	0_8	0.00	1.58	0.00	0_4	0.01	2.09	0.05	0_1	0.03	2.52	0.09
6	70	10	0_8	0.01	1.74	0.10	0_2	0.09	2.90	0.17	0_1	0.09	4.79	0.14
7	70	20	0_9	0.02	3.86	0.16	0_4	0.04	2.94	0.06	0.01	0.01	9.25	0.07
8	70	30	0_7	0.02	7.02	0.05	0_4	0.07	5.16	0.17	0_1	0.14	13.46	0.24
9	80	5	0_7	0.06	1.77	0.13	0_4	0.06	2.89	0.13	0_2	0.10	3.35	0.16
10	80	10	0_8	0.02	3.19	0.14	0_3	0.02	3.49	0.09	0_1	0.15	6.52	0.25
11	80	20	0_8	0.00	4.40	0.01	0_2	0.02	4.10	0.08	0.02	0.05	9.02	0.08
12	80	30	0_8	0.00	6.99	0.01	0_6	0.04	6.20	0.10	0.01	0.04	14.12	0.21
13	100	5	0_6	0.05	2.22	0.09	0_5	0.07	3.05	0.11	0_1	0.19	3.30	0.24
14	100	10	0_8	0.09	2.94	0.18	0_4	0.09	4.42	0.13	0.02	0.06	6.82	0.17
15	100	20	0_7	0.00	4.54	0.02	0_5	0.10	5.50	0.18	0.01	0.04	7.92	0.21
16	100	30	0_8	0.02	9.76	0.08	0_4	0.01	7.78	0.09	0.03	0.08	15.14	0.26

Table 3. ANOVA test for all methods

	Some of Square (SS)	Degree of freedom (df)	Mean Square (MS)	VR	F
Between groups (or "Factor")	428839.12	3	178231.68	9.2	2. 7
Within groups (or "Error")	2812889.66	108	21724.67		
Total	2293744.29	111			

$\upsilon = (S_1^2/n_1 + S_2^2/n_2)^2/(\frac{(S_1^2/n_1)^2}{n_1-1} + \frac{(S_2^2/n_2)^2}{n_2-1})$ degrees of freedom. The critical value of c is obtained from the relation Prob$(T > c)$= $\alpha = 0.05$. Table 4 shows this study. For more explanation, consider the results of Table 4, corresponds to the sample size=$n_1 = n_2 = 10$, μ_0=0, average FF for NGA and VNS are 59.74 and 60.60, respectively. Sample standard deviation for NGA and VNS are 2037 and 2.62, respectively. Since t=1.73>T=-0.77, we conclude that the difference is not statistically significant.

Table 4 demonstrated that NGA outperformed VNS in 62.5% of all classes and all of differences are statistically significant. Also, VNS outperformed NGA in 37.5% of all classes that in all cases, differences are statistically significant except one.

To do a deep comparison between NGA and VNS, Tukey honestly significance difference test can be used. It is a strong statistical tool to check significance by computing confidence interval similarly to the confidence interval

TABLE 4. Detail comparison between NGA and VNS

Class of problem	N_{max}	N_{min}	Ave. FF or $(\overline{X})$		Ave. SD or (S)		T	υ	t	Sig.
			NGA	VNS	NGA	VNS				
1	50	5	59.74	60.60	2.37	2.62	-0.77	18	1.73	NO
2	50	10	53.27	57.34	2.41	2.79	-3.48	18	1.73	Yes
3	50	20	72.04	62.42	2.19	2.25	9.70	18	1.73	Yes
4	50	30	75.92	58.11	2.60	3.39	13.18	17	1.74	Yes
5	70	5	71.61	48.73	2.96	3.16	16.70	18	1.73	Yes
6	70	10	78.56	59.93	2.66	2.68	15.58	18	1.73	Yes
7	70	20	72.77	60.86	4.19	4.84	5.88	18	1.73	Yes
8	70	30	57.49	67.77	4.50	4.36	-5.19	18	1.73	Yes
9	80	5	62.17	66.48	4.19	4.32	-2.27	18	1.73	Yes
10	80	10	80.73	62.01	3.68	4.56	10.10	17	1.74	Yes
11	80	20	83.93	66.05	4.29	3.89	9.75	18	1.73	Yes
12	80	30	74.14	62.98	3.63	4.14	6.41	18	1.73	Yes
13	100	5	61.58	67.47	4.82	4.83	-2.73	18	1.73	Yes
14	100	10	79.06	58.64	5.16	6.36	7.88	17	1.74	Yes
15	100	20	68.52	59.32	6.15	6.85	3.16	18	1.73	Yes
16	100	30	71.61	80.44	4.50	5.36	-3.99	17	1.74	Yes
Ave:Average, MS:Makespan, SD:Standard deviation, Sig:Significant										
Each class contains 10 independent instances										

for the difference of two means, but using the q distribution which avoids the problem of inflating α:

$$\bar{x}_i - \bar{x}_j \pm q\left(\alpha, r, df_w\right)\sqrt{\frac{MS_w}{2} \times \left(\frac{1}{n_i} + \frac{1}{n_j}\right)}$$

Table 5 summarized the outputs of this test.

TABLE 5. Tukey test results for NGA and VNS

	$\bar{x}_{NGA} - \bar{x}_{VNS}$	Critical q $q(\alpha,r,df_W)$	95% Conf Interval for $\mu_{HGA}-\mu_{LA}$		Significant at 0.05?
			Min	Max	
NGA-VNS	88.83	3.90	-69.06	69.11	Yes

6. Conclusion

In this research we introduced one population based meta-heuristic method for project selection problem. Presented method is based on the lifestyle of the Lion and simulated annealing's structure; therefore, we called it as new genetic algorithm (NGA). Initial population of solutions distribute between some groups (prides) and the best solution within each group called commander. Each child in each group (earned by mutation or crossover) challenge all commanders to substitute with worst member of group and be a new commander. After finite number of iterations, the best commander is the final solution. We used some heuristic mutation and crossover in NGA. Compared to basic genetic, NGA check more search spaces and yield more competitions between capable solutions, because of multi pupation technique and probabilistic rules. For the verification test, we recalled two powerful methods from the literature as Variable neighborhood search (VNS) and a hybrid TLBO-TS algorithm (HTT). Based on the comparison study, NGA works very competitive to solve multi-criteria portfolio selection problems.

References

[1] Afshar, M. Shahhosseini, V. Sabet, M. A genetic algorithm for subcontractors selection and allocation in multiple building projects, Soft computing, 25 (2021), pp. 11637–11652.

[2] Blum, C., Andrea, R. (2003). Metaheuristics in Combinatorial Optimization: Overview and Conceptual Comparison. ACM Computing Surveys, 35(3), pp. 268–308.

[3] Brester, C., Ryzhikov, I., Semenkin E., Multi-objective optimization algorithms with the island metaheuristic for effective project management problem solving, Organizacija, 50 (4) (2017), pp. 364-373.

[4] Carazo, A.F., Gómez, T., Molina, J., Hernández-Díaz, A.J., Guerrero, F.M., Caballero, R. Solving a comprehensive model for multi-objective project portfolio selection, Comput Oper Res, 37 (4) (2010), pp. 630-639.

[5] Davoudabadi, R., Mousavi, S. M., Šaparauskas, J., Gitinavard, H. (2019). Solving construction project selection problem by a new uncertain weighting and ranking based on compromise solution with linear assignment approach. Journal of Civil Engineering and Management, 25(3), 241-251.

[6] El-Ghazali, Talbi, (2009). Meta-heuristics, from design to implementation, published by John Wiley and Sons, Inc., Hoboken, New Jersey.

[7] Esfahani, H.N., hossein Sobhiyah, M., Yousefi, V.R., Project portfolio selection via harmony search algorithm and modern portfolio theory, Procedia-Soc Behav Sci, 226 (2016), pp. 51-58.

[8] Fernandez, E., Gomez, C., Rivera, G., Cruz-Reyes L., Hybrid metaheuristic approach for handling many objectives and decisions on partial support in project portfolio optimization, Inf Sci, 315 (2015), pp. 102-122.

[9] Kumar, M., Mittal, M., Soni, G., Joshi, D., A hybrid TLBO-TS algorithm for integrated selection and scheduling of projects, Comput Indus Eng, 119 (2018), pp. 121-130.

[10] Kumar, M., Mittal, M., Soni, G., Joshi, D. Selection and Scheduling of Interdependent Projects using a Modified Genetic Algorithm, f the International Conference on Industrial Engineering and Operations Management Bangkok, Thailand, March 5-7, (2019).

[11] Mohagheghi, V., Mousavi, M., Antucheviciene, J., Mojtahedi, M., (2019). Project portfolio selection problem: a review of model, uncertainty approaches, solution techniques

and case studies, Technological and Economic Development of Economy, 25(6), pp. 1380-1412.

[12] Nikkhahnasaba, M., Najaf, A., Project Portfolio Selection with the Maximization of Net Present Value, Journal of Optimization in Industrial Engineering 12 (2013), pp. 85-92.

[13] Nowak, M., Project Portfolio Selection Using Interactive Approach, Procedia Engineering, 57, (2013), PP. 814-822.

[14] Osman, I.H., Potts, C.N. (1989). Simulated annealing for permutation flow-shop scheduling. OMEGA, The International Journal of Management Science, 17, pp. 551–557.

[15] Panadero, J., Doering, J., Kizys, R., Juan, A.A., Fito, A., A variable neighborhood search simheuristic for project portfolio selection under uncertainty, J Heuristics (2018), pp. 1-23.

[16] Tofighian, A.A., Moezzi, H., Barfuei, M.K., Shafiee, M., Multi-period project portfolio selection under risk considerations and stochastic income, J Indus Eng Int, 14 (3) (2018), pp. 571-584.

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