EXPERIMENTAL DESIGN FOR GENETIC ALGORITHM SIMULATED ANNEALING FOR TIME COST TRADE-OFF PROBLEMS

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Abstract

Optimum solution of time cost trade-off (TCT) problem has significant importance for construction sector as it maximizes the profit of the project. As this is the case, numerous solution techniques are adopted for the optimum solution of TCT. Meta-heuristics are prevalent techniques for the adaptation of optimum solution of TCT. Meta-heuristic algorithms are problem independent algorithms; however their input parameters are sensitive to the problem type and are not immutable. Erroneous assignment of input parameters may abate the convergence to the optimum solution or even prevent the convergence to the optimum. In order to improve input parameters of the hybrid meta-heuristic algorithm; Genetic Algorithm with Simulated Annealing (GASA) an experimental design is implemented on an 18-Activity project. The correlation between the parameters and the sensitivity of the input parameters are revealed.

Keywords: Time Cost Trade-off, Genetic Algorithm, Simulated Annealing, Experimental Design

1. Introduction and Literature Review

Time Cost Trade off analysis is the compression of the project schedule to achieve a more favorable outcome in terms of project duration, cost, and projected revenues. The objectives of the TCT analysis are to compress the project until reaching the optimum duration which minimizes the total project cost.

TCT is one of the major interests of the construction management, since the optimum solution of TCT problem directly increases profit of the project. As this is the case, several algorithms and heuristics are developed and implemented which aims to achieve the optimum solution of TCT problems. Consequently, many researchers implement heuristic algorithms in their studies for the search of the optimum solution of TCT problem [1 -5]. Genetic Algorithm (GA) is also a well known heuristic method which has many implementations on the solution of TCT problem [6 – 25].

Although GA is a talented meta-heuristic algorithm, hybrid meta-heuristics can provide more successful results [26]. For this reason, many hybrid meta-heuristics are developed to improve the capability of GA and Genetic Algorithm with Simulated Annealing (GASA) is one of them. The adaptation of GASA for the solution of TCT problems presents successful results [27]. In this study, the model parameters of GASA are aimed to be improved by implementing experimental design. 18-Activity project is used for the tests of the design.

2. Methodology

The study consists of implementation of experimental design for a hybrid meta-heuristic algorithm, Genetic Algorithm Simulated Annealing (GASA). The meta-heuristic algorithms Genetic Algorithm (GA) and Simulated Annealing (SA) and experimental design are briefly introduced.

2.1 Genetic Algorithm

GA is a search technique used for finding exact or near optimum solutions to optimization problems. GA searches the global optimum with an algorithm based on the meiosis. An initial population is randomly generated and new genes are reproduced by crossover. The genetic differences are formed by mutation and the unfit genes are terminated by natural selection operations.

First step of the GA is generation of the initial population. Determining the population size has significant importance, because small populations contain the risk of seriously under-covering the solution space, while large populations incur severe computational demand. Binary representation is preferred for the solution of TCT where Goldberg indicates that the optimal size for binary-coded strings grows exponentially with the length of the string *n* [28]. By experimental design, population size is tried to be optimized.

Crossover is the necessary operation for the genetic reproduction. New genes are reproduced from randomly selected genes. Couples, namely the parents; are determined by randomly generated numbers and new two genes are reproduced from parents by crossover operation. The location of the crossover is also determined by generating a random number which is shown in Figure 1. After the crossover new two gene combinations are generated by the existing gene combination of the population.

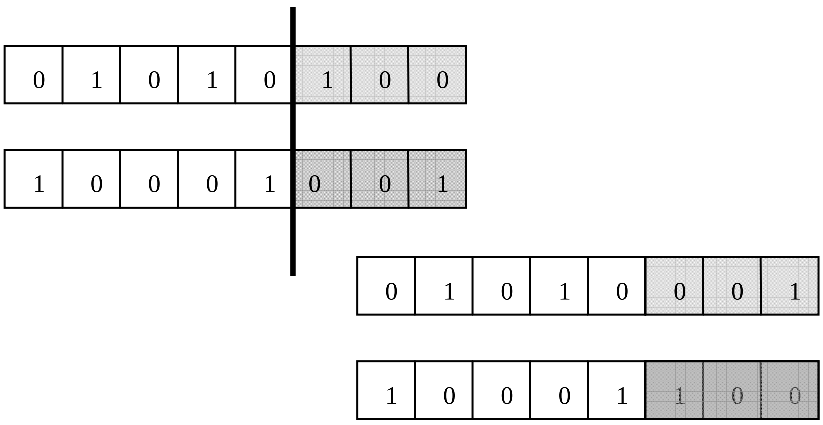

Fig.1. Crossover operator

Eshelman [29], worked on multipoint crossover that examined the biasing effect of traditional one-point crossover and considered a range of alternatives. Central argument was that two sources of bias exist to be exploited in a genetic algorithm; positional bias, and distributional bias. Eshelman concluded that simple crossover has considerable positional bias and the bias may be against the production of good solutions. In addition to this, crossover operator is analyzed in detail [30]. To prevent biased crossover, four point crossover is applied in this study.

Crossover rate has a vital importance that too low crossover rate can not produce enough genetic mixture and the convergence ratio decreases. Inversely, too high crossover rate too harshly mixes the genes and prevents the genes carrying good-fit chromosomes to converge into global optimum. Experimental design analysis includes the investigation of crossover rate as well. Mutation operator shifts the binary value of the gene on a randomly selected location from 0 to 1 or vice versa, which is shown in Figure 2.

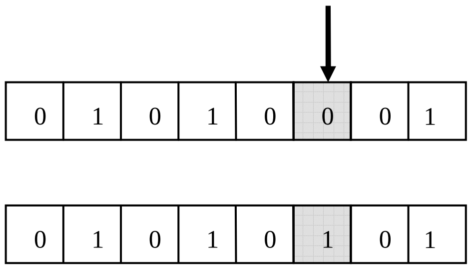

Fig. 2. Mutation operator

Mutation prevents domination of a certain gene which has high probability of survival. Initially domination of relatively good fit genes may cause being stuck into local minimum. On the other hand, too high mutation rate may also bastardize good fit genes. Moreover, crossover can produce good fit genes from existing genes, but it can not generate a new gene for a specific portion which does not exist in the population. Therefore, mutation operator has significant importance as it can produce new gene combinations, which have not been generated at the initialization of the population or regenerate a gene combination terminated at natural selection. Mutation rate is also important that too low mutation rate can not help to improve genetic diversity. However, too high mutation rate will be detrimental on the good fit genes and prevent convergence to optimum.

Natural selection is the final step of a cycle of the GA. Natural selection keeps the population size constant by terminating the same number of individuals reproduced at the crossover. In addition to this, it improves the overall gene quality of the population by terminating the low fit genes. On the other hand, low fit genes may carry very important genes on their certain location and in order to preserve these portions and prevent initially good fit genes to dominate, some precautions are taken at the natural selection phase. Roulette wheel selection algorithm has been implemented for this purpose which is a probabilistic selection algorithm. Roulette wheel determines the genes to be terminated by assigning high probability of termination to low fit genes and low probability of termination to good fit genes.

Natural selection operator completes the one cycle of the GA. Number of cycle generation depends on the number of input parameters and the expected reduction in the total project cost. Flowchart of GA is given in Figure 3.

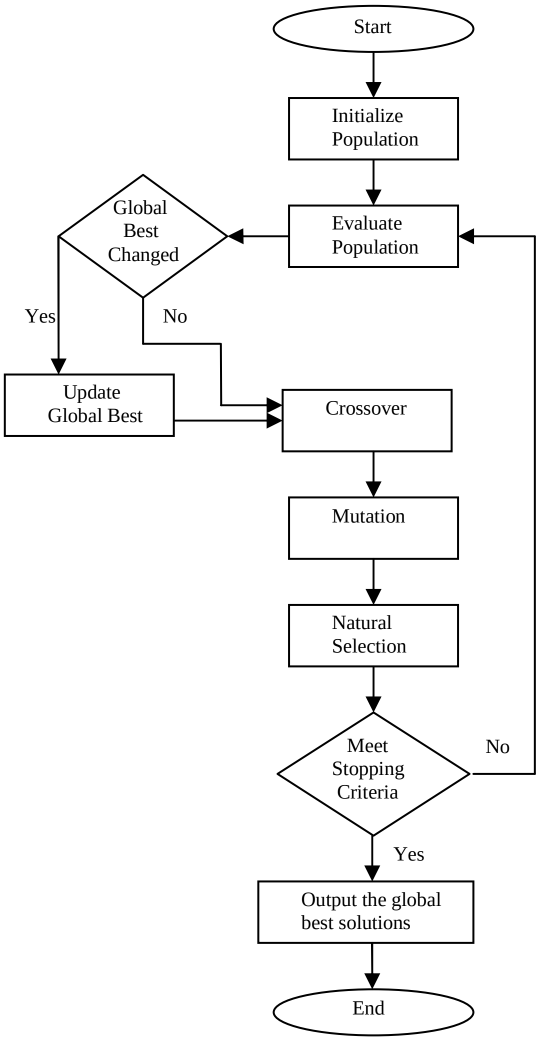

Fig. 3. Flowchart of GA

2.2 Genetic Algorithm with Simulated Annealing

If GA is implemented solely for the optimization, much iteration would be required to obtain satisfactory results. Convergence of GA can be increased significantly by applying complementary methods, thus important savings would be obtained in terms of computation time. Simulated Annealing (SA) is one of the complementary methods that are used for this purpose. SA is a generic probabilistic meta-heuristic algorithm for the global optimization problem. SA is inspired by the cooling schedule of alloys subjected to tempering. Initially, when the temperature is high, the molecules are free to move in any direction. At later phases, movements of molecules are restricted depending on the temperature [31].

Mutation operator sometimes leads to better genes and sometimes doesn’t. SA decides weather to reject or accept the mutation that leads to a worse result. The rejection probability increases as the iteration number increases which simulates the cooling of the alloy. SA accepts every mutation that leads to a better gene and decides the rejection of a harmful mutation.

Besides the initial temperature, the cooling schedule has vital importance as well. In theory, the temperature should be allowed to decrease to zero before the stopping condition is satisfied. However, in practice there is no need to decrease the temperature this far. Given the limited precision of any computer implementation, as t approaches zero from right, probability of accepting a harmful mutation will be indistinguishable to zero. Even before zero temperature is reached, it is likely that the chances of a complete escape from the current local optimum will become negligible. Thus the criterion for stopping can be expressed either in terms of a minimum value of the temperature parameter, or in terms of the 'freezing' of the system at the current solution.

If the initial temperature is not high enough or cooled very rapidly, there can be no beneficial mutations after a certain point. If no progress is apparent in searching, a concerted acceptance of detrimental mutation would be made in order to widen the scope of the search. Kirkpatrick [32] proposed reheating the temperature if there is not an improvement for a certain number of iterations. In this thesis study, there is not any reheating, by enlarging population size; enrichment of the gene content is aimed to be obtained.

The cooling process is controlled by Boltzmann Constant which is taken as 1 for GASA. Division by temperature for cooling is replaced by multiplying the exponential equation with the iteration number. After the mutation, a random number is generated for the decision and if the generated random number is smaller than the decision function, the mutation is accepted [33]. The decision function explained above is represented as:

$$Decision \quad \begin{cases} accepted \;\; if \;\; R_n \le e^{\frac{(f_m - f_0)t}{f_0 BC}} \\ rejected \;\; if \;\; R_n > e^{\frac{(f_m - f_0)t}{f_0 BC}} \end{cases}$$

where; R_n is a random number generated between 0 and 1 for the decision, f_m is the evaluation value of the mutated gene, f_0 is the initial value of the gene before the mutation operator affects the gene, BC is the Boltzmann constant used to determine the speed of cooling, t is the current number of iteration.

Decision function always gives results greater than 1 if the mutation is beneficial, as a result beneficial mutations are always accepted. If the mutated gene is worse than its initial state, the decision formula gives a result between 0 and 1 depending on the difference between the initial and mutated state. Higher the detriment of the mutation, closer the decision function to 0. If the detriment of the mutation is small the decision formula will give results close to 1 and the probability of acceptation will be high. Meanwhile, the higher the iteration number, the harder the acceptance criteria. If mutation is harmful even a small difference will be evaluated as close to 0 by the decision formula and the probability of acceptance will be very low. The hardening of acceptance criteria is controlled by the Boltzmann constant.

Genetic algorithm in which the acceptance of mutation is under the control of simulated annealing is called, Genetic Algorithm Simulated Annealing (GASA). The flowchart of GASA is given in Figure 4.

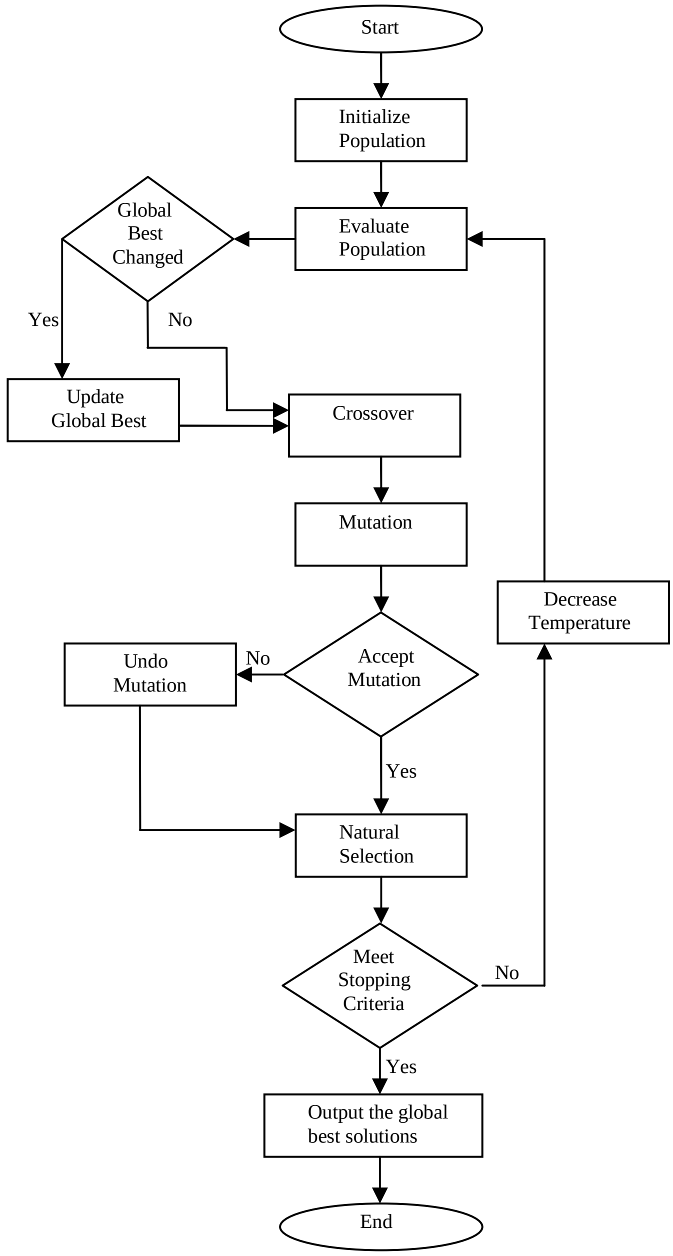

Fig. 4. Flowchart of GASA

2.3 Experimental Design

It is clear that the model parameters are correlated and affected by each other. As a result of this, it is difficult to guess the optimum or the suitable model parameter which will present the optimum solution in minimum number of schedule. In order to reveal the correlation between the parameters an experimental design is performed. The aim of this study is to measure the interaction between the basic parameters such as crossover, mutation, BC and population size. 18-Activity project is selected for the case study. The project is analyzed by considering the only 200$ constant overhead cost for each day with no delay penalty or early finish bonuses.

Experimental design is the systematic measurement of the responses of output variable based on the systematic changes on the input variables. *Variable* is a qualitative or quantitative entity that can vary or take on different values. *Reliability* is a crucial characteristic of measurement and refers to the consistency of a measuring device. *Validity* of an instrument means that it measures what it is designed to measure. *Control* involves holding constant or varying variables systematically so that, their effects can be removed from a study or compared to other conditions. *Randomization* refers to the assignment of subjects to conditions or levels of an independent variable either by the investigator or by a natural process in the field [34].

The design of an experiment should take; the objectives of experiment, the number of factors under investigation, possible presence of identifiable and non-identifiable extraneous factors, amount of time and money available for the experimentation into account [35]. In this study, boundaries of input variables are determined by obtaining the most common numbers from the literature. After determining the minimum and maximum values of the variable, experimental design analysis is performed by spreadsheet method.

Main effect of a dependent variable on the independent variable is defined as the difference in the average response between the high and low levels of a factor. The main effect can be represented as [36];

$$E(A) = \bar{Y}_{A^+} - \bar{Y}_{A^-} \tag{1}$$

Where, $E(A)$ is the effect of dependent variable A on the independent variable, $\bar{Y}_{A^+}$ is the average response of the high level, $\bar{Y}_{A^-}$ is the average response of the low level of A.

Interaction occurs when a particular combination of two factors affect the dependent variable unexpectedly from simply observing their main effects. Interaction is defined as one-half of the difference between the effect of independent variable A at the high level of B and the effect of A at the low level of B. The interaction of dependent variable A and B can be formulated as [36];

$$E(AB) = \frac{1}{2}\left[\left(\bar{Y}_{A^+} - \bar{Y}_{A^-}\right)_{B+} - \left(\bar{Y}_{A^+} - \bar{Y}_{A^-}\right)_{B-}\right] \tag{2}$$

where, $\left(\bar{Y}_{A^+} - \bar{Y}_{A^-}\right)_{B+}$ is the effect of A when B is high and $\left(\bar{Y}_{A^+} - \bar{Y}_{A^-}\right)_{B-}$ is the effect of A when B is low.

In order to determine the significance of the independent parameters and their interactions between each other, t-test is performed. Determination of significance requires calculation of standard deviation as a measure of inherent variation or experimental error in the process. Variance is the square of the deviation of each observation of a sample from the sample average which can be written as [36];

$$S^2 = \frac{\sum \left(X_i - \bar{X}\right)^2}{n-1} \tag{3}$$

Average variance is the average of the variance of each variance obtained by k runs, where k is equal to 2^n if there are n investigated independent variables with only high and low levels. Average variance is computed as following;

$$S_e^2 = \sum S_i^2 \tag{4}$$

Effects of the dependent variables are differences between averages and require definition of a modified variation which is called variation of the effects as [36];

$$S_{eff}^2 = S_e^2 \frac{4}{N} \tag{5}$$

where N is the total number of trials. As long as the factors will have only high and low levels equation 4.5 will be valid.

In order to perform t-test, degrees of freedom of the data set should be determined. The computation of degrees of freedom is shown below [37];

$$d.f. = (\#\ of\ \ observations\ \ per\ run - 1) \times (\#\ of\ \ runs) \tag{6}$$

Next step is selecting a significance level for the t-test. In this analysis 95% significance interval is preferred. By using the significance interval and degrees of freedom, t-value is obtained and decision limits are calculated by the formula [37];

$$DL = \pm (t_{\alpha,df})(\sigma_{\alpha,df}) \tag{7}$$

If effect of a variable or interaction is outside the region defined by DL, then the variable or interaction is determined as significant. The model parameters are adjusted according to the significances of them. However, the relationships of the parameters are not always linear which makes interpolation not applicable.

3. Experimental Design of 18-Activity Project

18-activity project is analyzed for experimental design of GASA. Population size, crossover, mutation and BC are analyzed. The project cost at the end of 50000^{th} schedule is taken into account in order to make a fair comparison of the effect of the parameters. The crashing options of the activities and logical relationships between the activities are shown in Table 1 [38].

Since there are four parameters number of interactions and parameters becomes $2^4 = 16$. Each run is repeated 10 times in order to obtain redundant observations. As a result of this, there are (10 – 1)* 16 = 144 redundant observations.

In Figure 5 pareto chart of effects of GASA for the 18-activity project is shown. The bars show the effect of the parameter on the total cost of the project. The most significant parameter is the population size where if population size is increase total project cost at the end of the 50000^{th} schedule also increase. Similarly, when crossover ratio and Boltzmann Constant is increased total project cost also increases. There is significant interaction between the parameters population size and crossover, population size and Boltzmann Constant and

Crossover and Boltzmann Constant. As this is the case the interaction between the three parameters are also significant. The positive interaction means that when the population size and crossover rate is increased simultaneously, the increase in total project cost will be more than the prediction by only considering increase in total project cost when these two parameters are increased solely.

Table 1. 18-Activity Project

Act. No.	**Predecessor**	**Alternative 1**		**Alternative 2**		**Alternative 3**		**Alternative 4**		**Alternative 5**	
		Dur. (days)	Cost ($)	Dur. (days)	Cost ($)	Dur. (days)	Cost ($)	Dur. (days)	Cost ($)	Dur. (days)	Cost ($)
1	–	14	2,400	15	2,150	16	1,900	21	1,500	24	1,200
2	–	15	3,000	18	2,400	20	1,800	23	1,500	25	1,000
3	–	15	4,500	22	4,000	33	3,200	–	–	–	–
4	–	12	45,000	16	35,000	20	30,000	–	–	–	–
5	1	22	20,000	24	17,500	28	15,000	30	10,000	–	–
6	1	14	40,000	18	32,000	24	18,000	–	–	–	–
7	5	9	30,000	15	24,000	18	22,000	–	–	–	–
8	6	14	220	15	215	16	200	21	208	24	120
9	6	15	300	18	240	20	180	23	150	25	100
10	2, 6	15	450	22	400	33	320	–	–	–	–
11	7, 8	12	450	16	350	20	300	–	–	–	–
12	5, 9,10	22	2,000	24	1,750	28	1,500	30	1,000	–	–
13	3	14	4,000	18	3,200	24	1,800	–	–	–	–
14	4, 10	9	3,000	15	2,400	18	2,200	–	–	–	–
15	12	12	4,500	16	3,500	–	–	–	–	–	–
16	13, 14	20	3,000	22	2,000	24	1,750	28	1,500	30	1,000
17	11, 14, 15	14	4,000	18	3,200	24	1,800	–	–	–	–
18	16, 17	9	3,000	15	2,400	18	2,200	–	–	–	–

Variables to be examined and their low and high limits are given in Table 2.

Table 2. High and Low levels of parameters of GASA

Parameter	**High Level**	**Low Level**
Population Size (A)	200	50
Crossover (B)	0,9	0,3
Mutation (C)	0,9	0,3
Boltzmann Constant (D)	1,5	0,5

It is seen that increasing mutation rate decreases the total project cost at the end of the 50000th schedule. Consequently, in order to obtain near-optimum results at the end of the 50000th schedule low level values should be assigned to the population size, crossover and Boltzmann constant and high level value should be assigned to mutation.

The examined four parameters have significant effect on the computational demand. Whole second order correlations except for the correlation between the mutation and BC are also significant. The second order correlations have the same sign with the multiplication of the correlated parameters which also increases the effect of the parameters.

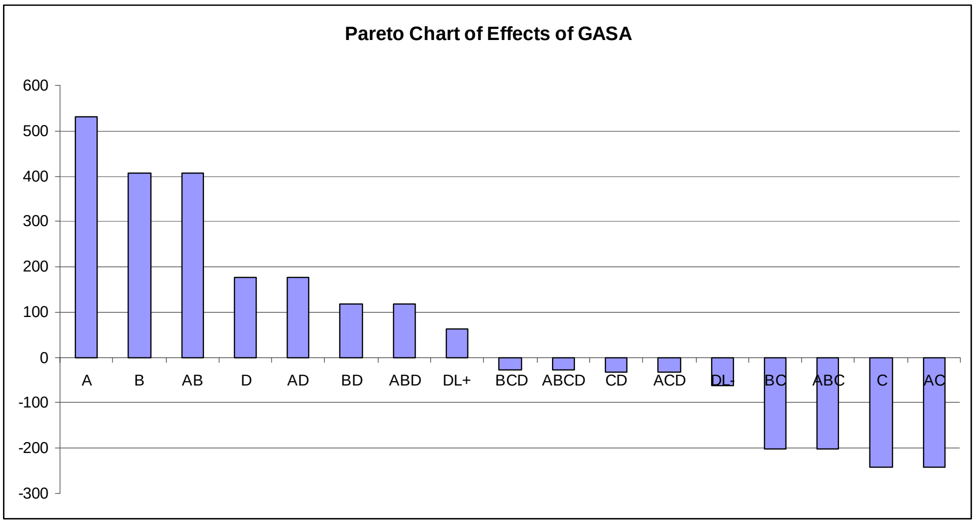

Fig. 5. Pareto Chart of effects of GASA

4. Conclusion

In this study, model parameters of a meta-heuristic algorithm are adopted for solution of medium sized TCT problems. It is seen that the meta-heuristic algorithm can already find the optimum the problem; however by improving the model parameters the optimum solution is obtained in shorter computational duration.

Computation duration for the execution of 50000 iterations is around 2 seconds which does not seems to be important to bother for improving the input parameters. However, it is known that the number of required generations would increase exponentially with the project size. As a result of this, improving the input parameters for GASA would end up with saving of hours in terms of computational duration for larger projects.

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