

Impact of Genetic Algorithm Operators in Solving Resource-Leveling Problem



R. S. Gokula Krishnan and Gopinath Selvam

Abstract Resource leveling reduces the peak fluctuations in the resource requirement. Fluctuation in the resource requirement leads to construction delays, frequent hiring and firing of labors which affects labor productivity during the execution of the project. Resource-leveling problem (RLP) is a type of combinatorial problem that requires advanced problem-solving approaches to solve. Genetic algorithm (GA) is one of the well-adopted meta-heuristic approaches to solve combinatorial problems like RLP. The objective of this study is to determine the impact of different values of genetic algorithm operators from previous literature works to obtain the optimal values to perform genetic algorithm operations. A real-time construction project data is considered to study the relationship of genetic algorithm operators which leads to determining the optimal values.

Keywords Resource leveling · Genetic algorithm · Labor productivity · GA operators

1 Introduction

In the construction industry, project management plays a crucial role in handing over the project on time and this depends on handling the various resources efficiently [1]. Resource-leveling problem (RLP) is considered the most critical phase in managing the project [2]. Resource leveling focuses on utilizing the resources efficiently where the duration is a constraint, and it minimizes deviation in daily resource requirement to the possible extent [3]. When the variation in resource requirement reduces, automatically the resource demand and the cost of the project decreases [1].

R. S. G. Krishnan (✉) · G. Selvam
Department of Civil Engineering, SRM Institute of Science and Technology, Chengalpattu district, Kattankulathur, Tamil Nadu 603203, India
e-mail: gr4655@srmist.edu.in

G. Selvam
e-mail: gopinats@srmist.edu.in

Resource leveling takes place after scheduling the project in which the objective is to minimize the fluctuation of the resource. The resource-leveling solution can be found by shifting the non-critical activity. The critical path method (CPM) is the technique that is generally used to schedule the project activities by considering the precedence relationship [4]. Traditional approaches give solutions when the number of activities is less; similarly, heuristic approaches give solutions for larger projects but the problem is that these approaches will not provide an optimal solution or near-optimal solution and when the number of activities increased these approaches take a long time to resolve [10].

Resource leveling is considered the most important factor in project management in which it defines the profit and success of the project [5]. Resource leveling was done in various approaches to minimize the project's peak resource requirement. These approaches gave a better solution, but a complex project to deal with it took a long time. In resource-leveling problem, duration is the constraint where the project duration is not extended at any cause. Resource leveling is done to reduce the variation in the resource requirement throughout the project duration. The process of resource leveling is done by shifting the early start of the non-critical activities [6].

2 Genetic Algorithm

Genetic algorithm was invented by John Henry Holland in the 1970s. It is purely based on Charles Darwin's theory of natural selection. It consists of six phases. They are initial population where it refers to the set of possible solutions, and the second phase is the fitness function where each possible solution has a fitness score. The third phase is the selection process. This process is done by Roulette wheel, based on the fitness score it moves to the recombination process. The fourth phase is recombination. During the process of recombination, chromosomes might face random changes in the gene. Genes are joined into a string to form a chromosome. Good characteristics of the population get transferred to the next generation [7]. The fifth phase is the mutation where at a random point changes take place in the gene. In this phase, the changes that take place in a positive manner move to the next generation; otherwise, the gene will not transfer to the next generation. Good genes and good features will be transferred from one generation to the next generation. The final process is elitism where the fittest individual guaranteed will not undergo mutation. These processes are repetitively done over the generation until we get the optimal solution.

3 Research Gap

Genetic algorithm optimization was the most preferred method to solve the resource-leveling problem (RLP) [8] since the nature of RLP and genetic algorithm (GA) is similar. GA is a meta-heuristic approach in which it consists of six stages, including

four operators—initial population, selection, fitness function, recombination, mutation and elitism. Previously the authors who solved the RLP using GA had come across these operators. In the proposed study, the selection process is done by the Roulette wheel method and then the different values were assigned to the operators to obtain the optimal solution. This paper presents the variant values for each operator to know how the different values of each operator influence the determination of optimal solution.

4 Literature Review

An idea is proposed to use genetic algorithm in solving the resource-leveling problem in order to overcome the difficulties faced in traditional and heuristic approach, which were complex to solve larger data and it had a limitation on computation time [1]. Genetic-algorithm-based resource-leveling scheduling system is used to illustrate the approached problem [1]. An idea is stated to control the pollution caused due to the execution of construction by resource leveling [9]. Here, the author introduces new parameters such as construction pollution index (CPI) and hazard magnitude (h_i). These were considered pseudo-resource [9]. If the level of pollution increases the limit assigned by the government, then it is founded by the regulatory body; hence, resource leveling is done to distribute the pollution evenly [9]. Reference [10] A model was adopted to use a hybrid GA for scheduling the resources in construction projects in which it considers all precedence relationships; the presented algorithm showed good performance over the traditional critical path method (CPM) by reducing the cost, minimizing the project schedule.

This paper affirmed a new GA that enables the multi-objective technique to level multi-resource. In this GA model, each resource usage is founded by adaptive weights where it is generated from the previous generation [11]. In this process, the GA model and the method of moving asymptotes (MMA) approach were compared where GA showed better solutions as it can be used to optimize larger projects [11]. A new approach is proposed using GA and Monte Carlo simulation to level the resource by developing a model under uncertainty. The project networks were modeled by Monte Carlo simulation and the GA is used to level the multi-resource to get maximum usage of resource under minimum duration [12]. This paper proposed a new concept of RLP with relationship options and it provides an alternative relationship that offers more float time and allows new possibilities to arrange in an efficient pattern and minimizes the project resource demand. This model can be used directly to level multiple resources [4]. The model is verified with two project instances. From both instances, it was concluded that the RLP model with options gave better results than the model without relationship options [4]. The presentation of this paper involves an algorithm based on hyper-heuristic which is a tabu-based search for problems in resource leveling under the circumstances of resource constraints. By using the concept of “replace” and “swap” in the priorities of work, “hard core” has not been changed in the hyper-heuristic algorithm [13]. Therefore, the result proves that this

algorithm will improve resource handling under resource constraints [13]. This paper deals with resource-leveling optimization problem met in modern project management and it is comparatively analyzed with three different intelligent meta-heuristics by hybrid nature-inspired intelligent approach, and a combination of ant colony optimization (ACO) and genetic algorithm here proves to be a more effective approach in making a special decision [14]. This paper proposed the development of two resource-leveling metrics to assess and mitigate the negative effects of resource volatility on construction efficiency and cost. This shows that the developed metrics are capable of reducing unfavorable resource fluctuation and resource idle time [15]. In previous research, authors have used different values for each operator and concluded the optimal solution for their approached problem. In this study, the different values of each operator are assigned and their results are compared and from that the optimal solution is obtained.

5 Methodology

Figure 1 shows the procedure for carrying out the proposed idea. The real-time construction project data was considered to solve the proposed idea. Then the activities were determined from which the resources were allocated to each activity and the resource profile was prepared. From the given activities, the non-critical activities were determined. The GA model is created in the MATLAB 2016a. The input data got from the resource profile is implemented in the GA model. The parameters are defined until an optimal solution is obtained. A real-time construction project data of G + 1 residential building located in Chennai, which consists of 18 activities is used to study the effectiveness of the optimal values. The resources were allocated according to the quantity of work to be done. The data was then implemented in the Microsoft project management (MSP) through which the critical, non-critical activity and total float days were calculated.

Once the data is collected, the quantity of the amount of work to be done should be calculated. The duration for each work was allocated according to the amount of work to be done and it depends on the amount of resource availability. The resources were allocated to each activity, and the activity predecessors are also mentioned. The critical, non-critical activity and float days were calculated by implementing the data in MSP. The daily resource requirement was then calculated by acquiring the data from the MSP and implementing it to MS-Excel. The acquired data is implemented into the MATLAB 2016a, and then using genetic algorithm optimization, resource leveling is done. Finally, the daily resource requirement after leveling is acquired (Table 1).

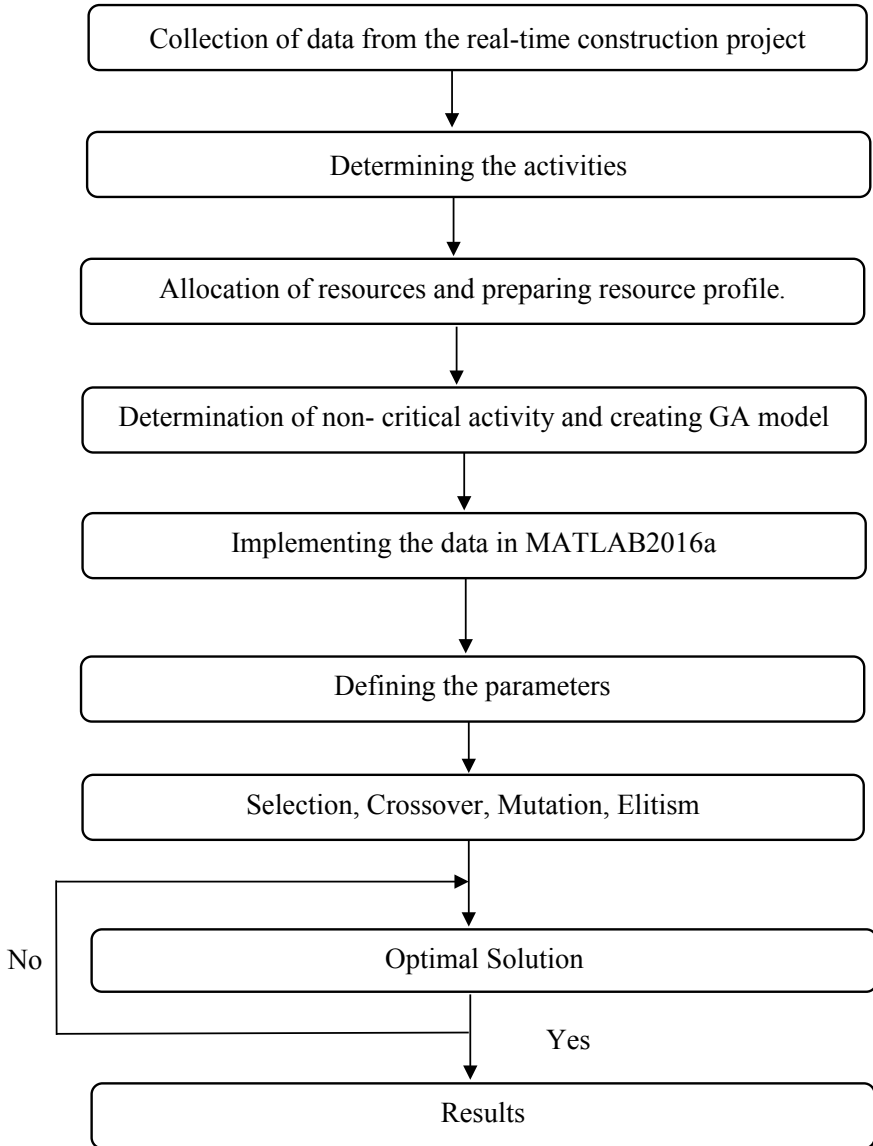


Fig. 1 Methodology

6 Results and Discussion

The parameters considered to obtain the solutions are the probability of crossover (P_{cr}), probability of mutation (P_m), and probability of elitism (P_{er}). The convergence curve shows the attainment of the optimal solution where the x-axis denotes the

Table 1 Activity details

S. no.	Task name	Precedence	Duration	Mason	Helper	Carpenter	Fitter	Bhisti
1	<i>Column casting</i>							
2	Reinforcement		14	–	15	–	10	–
3	Shuttering	2SS+1 days	8	–	8	15	–	–
4	Concreting	2,3	4	10	15	–	–	20
5	De-shuttering	4FS+1 days	2	–	15	17	–	–
6	<i>Beam casting</i>							
7	Reinforcement	5FS	13	–	8	–	4	–
8	Shuttering	7SS+2 days	6	–	10	13	–	–
9	Concreting	7,8	4	10	15	–	–	20
10	De-shuttering	9FS+1 days	1	–	10	13	–	–
11	<i>Floor slab</i>							
12	Shuttering	10FS	10	–	5	2	–	–
13	Reinforcement	12SS+2 days	14	–	6	–	10	–
14	Strand laying	13SS+1 days	4	–	10	–	13	–
15	Reinforcement	13SS	10	–	5	–	6	–
16	Concreting	13,14,15	4	15	90	–	–	55
17	Stressing of strands	16FS+18 days	4	–	30	–	30	–
18	De-shuttering	16FS+14 days	2	–	26	15	–	–

number of generations and the y-axis denotes the optimal solution The graph shows the number of iteration done for each trial and it shows the significant changes in obtaining the optimal solution (Z). Five trials were done to attain the optimal solution from the input data we got from the real-time construction project data. The objective is to keep the duration as the constraints we need to level the resource without affecting the project’s even flow.

Table 2 shows the variant values of each operator and their optimal solution. Figure 3 shows their respective operator input values and their optimal solution. In Fig. 2, the optimal solution is attained at the ninth generation and in Fig. 3 the

Table 2 Different operator’s values and its respective optimal solution

Trial no.	Pcr	Pm	Pel	Z
1	0.85	0.03	0.01	–351188
2	0.90	0.01	0.2	–352100
3	0.95	0.01	0.2	–351204
4	0.85	0.02	0.02	–351188
5	0.85	0.02	0.01	–351284

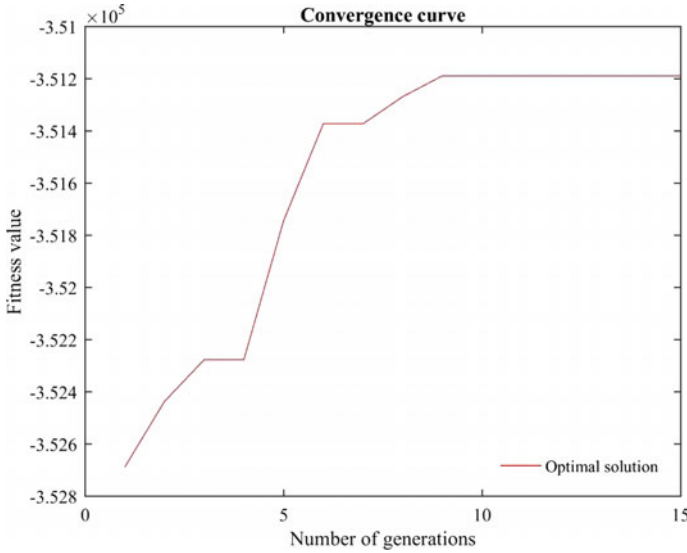


Fig. 2 Trial 1— $P_{cr} = 0.85$, $P_m = 0.03$, $P_{er} = 0.01$, $z = -351,188$

optimal solution is attained at the fifth generation. In Fig. 4, the optimal solution is attained at the seventh generation. In Fig. 5, the optimal solution is attained at the 12th generation. In Fig. 6, the optimal solution is attained at the 14th generation. The maximum iteration considered was 15 where we found the optimal solution by varying the values of the different operators. The bar chart shows the daily resource requirement of the schedule throughout the project.

The bar chart (Fig. 7) shows the resource histogram before leveling. Figs. 8, 9 and 10 show the after leveling profile of their respective trials and its significant changes occur in the resource requirements for each trial. The objective is to keep the duration as the constraints and we need to level the resource without affecting the project’s even flow.

7 Conclusion

This study is done to determine the impact of different values of genetic algorithm operators to obtain the optimal solution. From the conducted trials, the optimal solution is $z = -352,100$ for which the value of the defined parameters is $P_{cr} = 0.90$, $P_m = 0.01$, $P_{el} = 0.2$. The optimal solution is obtained from the fifth iteration. The optimal solution is obtained in lesser iteration. It shows the relationship between the different GA operators from the conducted trials by their respective optimal solutions.

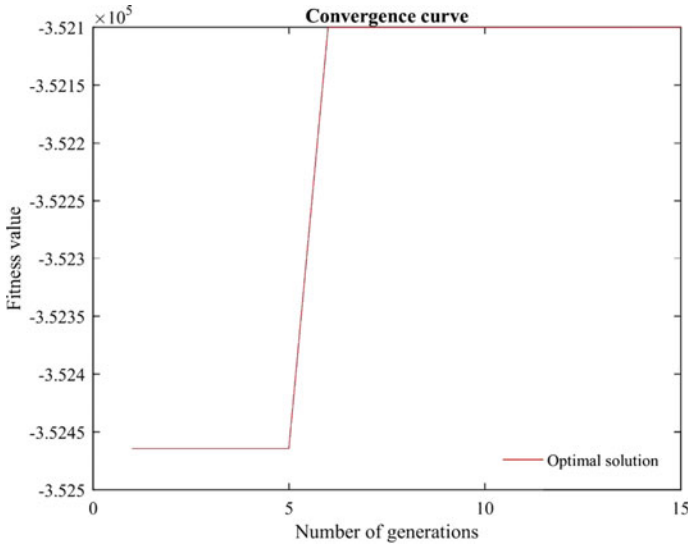


Fig. 3 Trial 2— $P_{cr} = 0.90$, $P_m = 0.01$, $P_{er} = 0.2$, $z = -352,100$

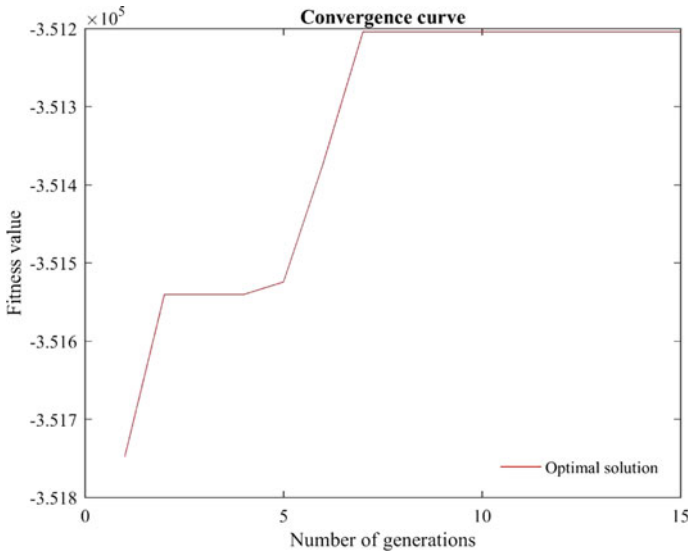


Fig. 4 Trial 3— $P_{cr} = 0.95$, $P_m = 0.01$, $P_{er} = 0.2$, $z = -351,204$

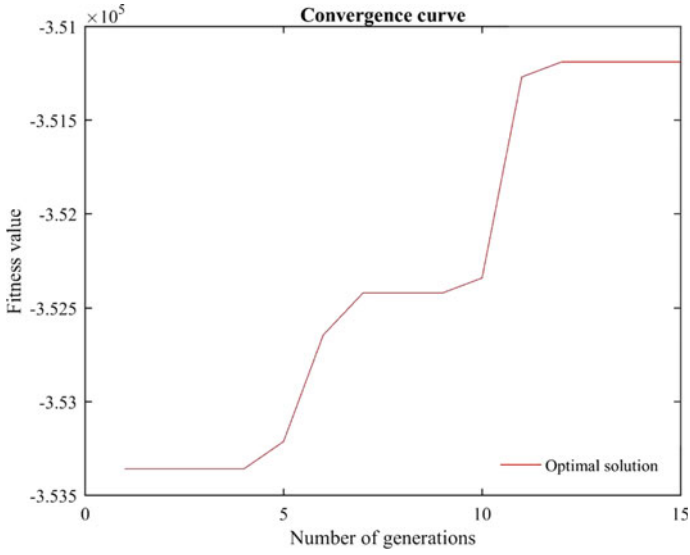


Fig. 5 Trial 4— $P_{cr} = 0.85$, $P_m = 0.02$, $P_{er} = 0.01$, $z = -351,188$

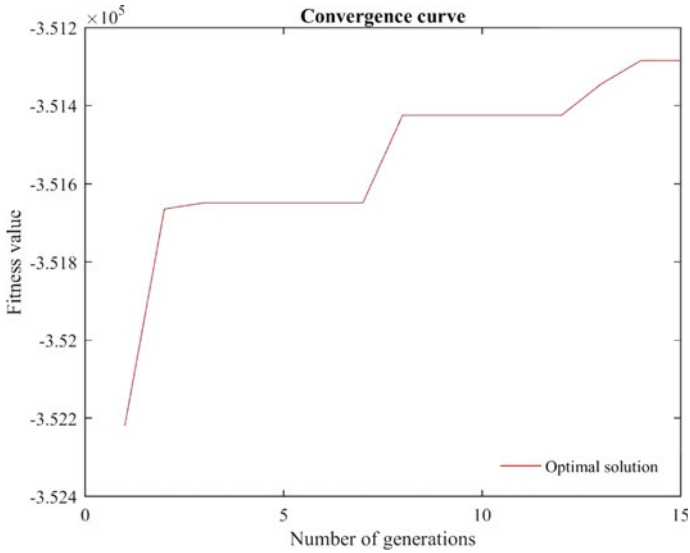


Fig. 6 Trial 5— $P_{cr} = 0.85$, $P_m = 0.02$, $P_{er} = 0.01$, $z = -351,284$

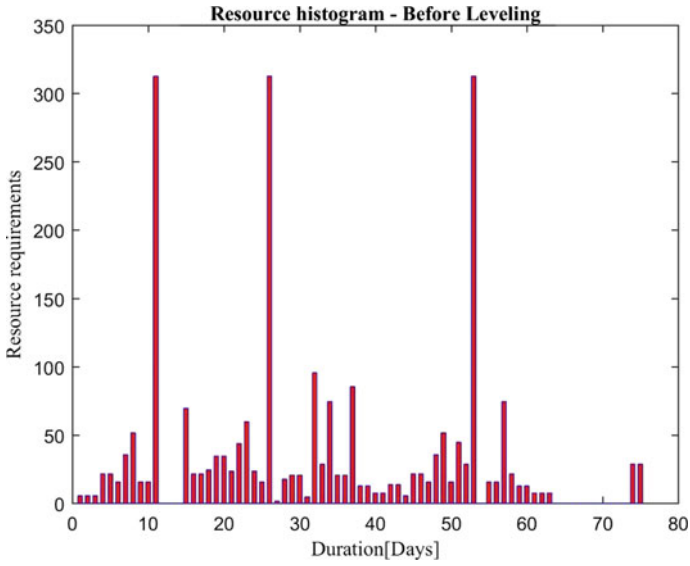


Fig. 7 Before leveling

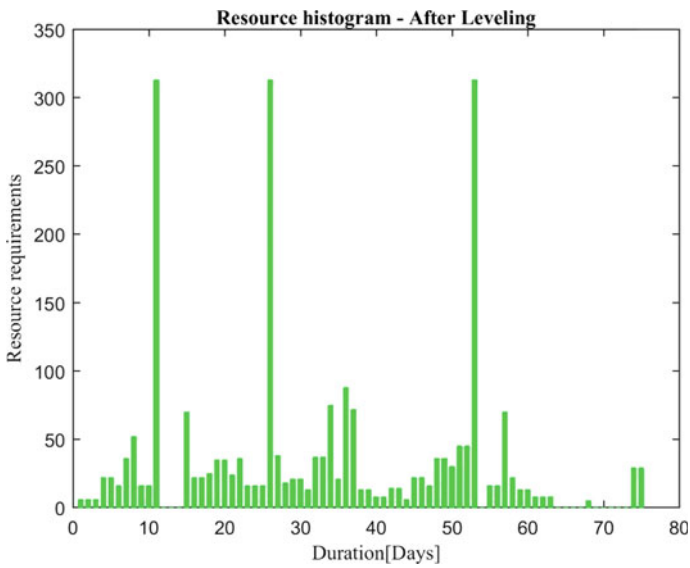


Fig. 8 Trial 1—After leveling

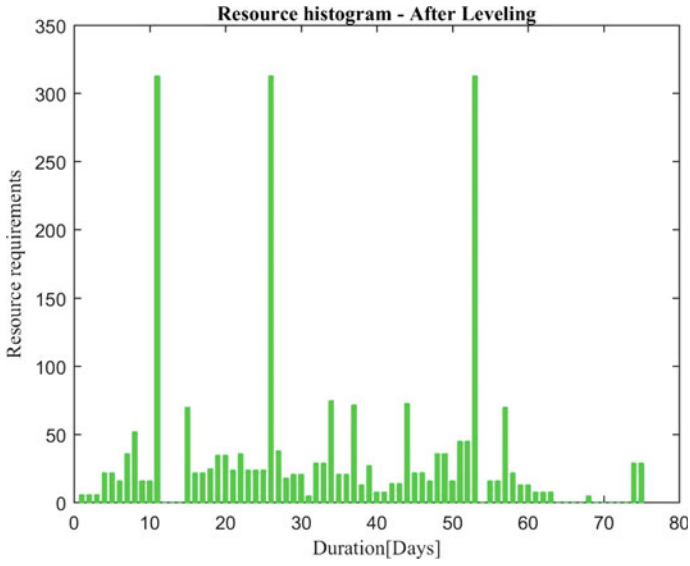


Fig. 9 Trial 2—After leveling

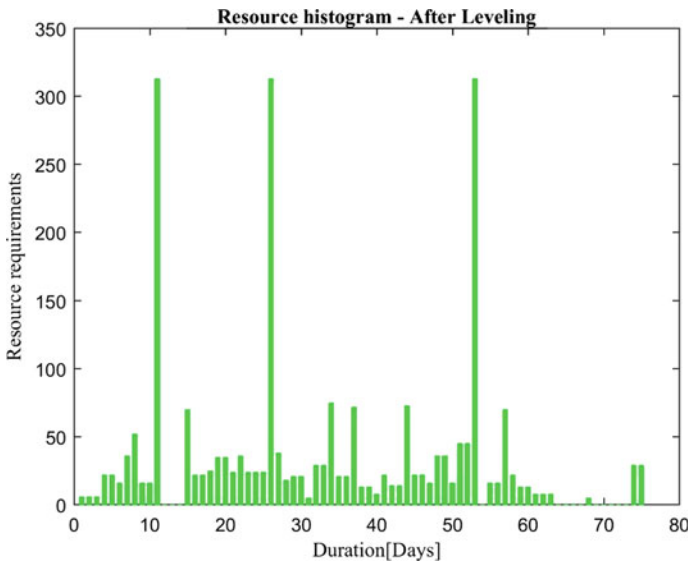


Fig. 10 Trial 3—After leveling

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