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Optimization of Construction Project Scheduling using Metaheuristic Algorithms

Anubha Sahu, Mrs. Ragini Mishra
Babulal Tarabai Institute of Research and Technology, Sagar Madhya Pradesh

Abstract
A new approach for resource scheduling using genetic algorithms (GAs) is presented here. The methodology depend on any set of heuristic rules. Instead, its strength lies in the selection and recombination tasks of the GA to learn the domain of the specific project network. By this it is able to evolve improved schedules with respect to the objective function. Further, the model is general enough to encompass both resource leveling and limited resource allocation problems unlike existing methods, which are class-dependent. In this paper, the design and mechanisms of the model are described. Case studies with standard test problems are presented to demonstrate the performance of the GA-scheduler when compared against heuristic methods under various resource availability profiles. Results obtained with the proposed model indicate an exponential batter result in the computational time required for larger problems.

Keywords: optimization; construction time; scheduling; reliability; random term extension factors; project interruptions; evolutionary modelling

I. Introduction

The construction industry is leading as the topmost contributor to India's GDP (Gross Domestic Product). The Project Management Institute (PMI, 2008) defines a construction project as ''a temporary endeavor addressed to create a distinctive product, service, or result''. It provides a greatest employment provision beyond supporting economic potential. According to the reports of the Government, the construction sector has been travelling continuously on a constant growth path, even though innumerable challenges are forwarding march in restraining the development of construction industry. Scheduling is an unavoidable event to cramp the success of any production process in any industry. It is well known that the scheduling under the indoor environment (Manufacturing industry) industries is more successful than the outdoor environment industry like construction industry (building construction, road works, railways, and civil engineering structures etc.).

II. Importance Of Construction Scheduling

A construction schedule is defined as a calendar which connects the assigned tasks with the resources required to perform the tasks. It is used to determine the time and sequence of operations of the construction projects. It calculates the start or end of a specific activity and it assembles the various operations or tasks throughout the project to present a clear picture from the beginning to the completion of the project. A well planned construction schedule guides in outlining the assigned jobs and also defines the methods and sequence in which the materials are going to be put in place. A scheduler must take care in designing the right schedule by considering all the important factors in mind. Scheduling evaluates the sequence of activities to allocate various resources required for the tasks. The scheduler is the key person involved in making the schedules in a typical construction project. The start and end date of an activity depend on its duration, predecessor activity, predecessor relationships, resource availability, and finishing date of the project. Fig. 1.1 shows the different stages or phases involved in construction planning.

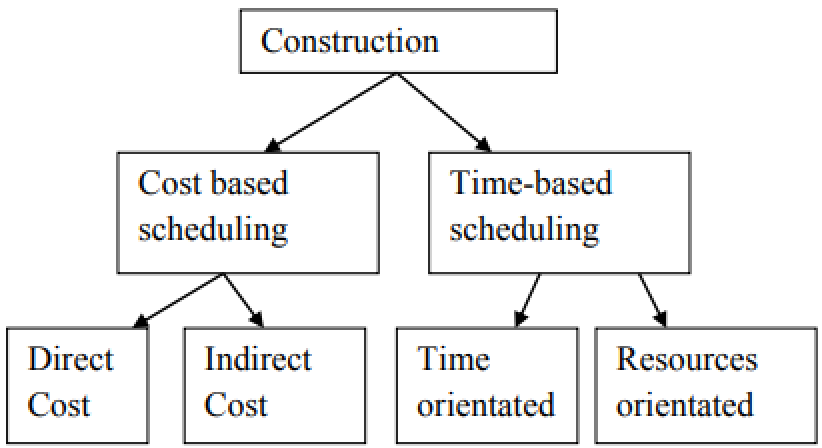

Fig.1.1 Different phases of Construction Planning

Construction planning is considered as two ways of approach, first cost oriented scheduling and second is time oriented scheduling method. Cost orientated scheduling is based on the budget and availability of cash flow in the project. Time oriented scheduling is based on time or resource orientated scheduling. Nowadays most of the projects follow time based scheduling.

Scheduling Model

Globally, the construction projects are considered as wheel of vehicle of economic growth and development. One of the most significant challenges in construction industry is keeping projects on track and under control so that they are completed according to the objectives established by stakeholders during the planning phase. The major objectives of construction projects are to complete them successfully within estimated time and cost, optimum amount of resources, minimum safety risks and environmental impact along with achieving the satisfactory project quality. To meet this challenge, the presented study is conducted to develop a robust multi-objective scheduling model (RMOSM) for civil construction projects using metaheuristic approaches. To control execution of a construction project, the study also suggests a method to

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reschedule the project if it deviates from its original schedule. Furthermore, the present study includes a statistically based analysis of factors causing delays in Indian highway projects being developed under Hybrid Annuity Model (HAM). In introduction chapter, background, motivation, objectives, methodology and scope of the study are described in detail. Thesis organization is presented in the last part of the chapter which includes chapter wise brief description of thesis

As a global optimization search algorithm, genetic algorithm is simple and easy to use, and it can solve the optimization problem more easily and satisfactorily, and it is widely used in various optimization problems and models such as artificial intelligence.

III. Proposed Methodology Genetic Algorithm

In computer science and operations research, a genetic algorithm (GA) is a metaheuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA).[1] Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems via biologically inspired operators such as selection, crossover, and mutation.[2] Some examples of GA applications include optimizing decision trees for better performance, solving sudoku puzzles,[3] hyperparameter optimization, and causal inference.[4]

Optimization problems

In a genetic algorithm, a population of candidate solutions (called individuals, creatures, organisms, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible.[5]

The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a generation. In each generation, the fitness of every individual in the population is evaluated; the fitness is usually the value of the objective function in the optimization problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

A typical genetic algorithm requires:

a) a genetic representation of the solution domain,
b) a fitness function to evaluate the solution domain.

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A standard representation of each candidate solution is as an array of bits (also called bit set or bit string).[5] Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming; a mix of both linear chromosomes and trees is explored in gene expression programming.

Once the genetic representation and the fitness function are defined, a GA proceeds to initialize a population of solutions and then to improve it through repetitive application of the mutation, crossover, inversion and selection operators.

Initialization

The population size depends on the nature of the problem, but typically contains hundreds or thousands of possible solutions. Often, the initial population is generated randomly, allowing the entire range of possible solutions (the search space). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found or the distribution of the sampling probability tuned to focus in those areas of greater interest.[6]

Selection

During each successive generation, a portion of the existing population is selected to reproduce for a new generation. Individual solutions are selected through a *fitness-based* process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as the former process may be very time-consuming.

The fitness function is defined over the genetic representation and measures the *quality* of the represented solution. The fitness function is always problem-dependent. For instance, in the knapsack problem one wants to maximize the total value of objects that can be put in a knapsack of some fixed capacity. A representation of a solution might be an array of bits, where each bit represents a different object, and the value of the bit (0 or 1) represents whether or not the object is in the knapsack. Not every such representation is valid, as the size of objects may exceed the capacity of the knapsack. The *fitness* of the solution is the sum of values of all objects in the knapsack if the representation is valid, or 0 otherwise.

In some problems, it is hard or even impossible to define the fitness expression; in these cases, a simulation may be used to determine the fitness function value of a phenotype (e.g. computational fluid dynamics is used to determine the air resistance of a vehicle whose shape is encoded as the phenotype), or even interactive genetic algorithms are used.

Genetic operators

The next step is to generate a second generation population of solutions from those selected, through a combination of genetic operators: crossover (also called recombination), and mutation.

For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. By producing a "child" solution using the above methods of crossover and mutation, a new solution is created which typically shares many of the characteristics of its "parents". New parents are selected for each new child, and the process continues until a new population of solutions of appropriate size is generated. Although reproduction methods that are based on the use of two parents are more "biology inspired", some research [7][8] suggests that more than two "parents" generate higher quality chromosomes.

These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally, the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions. These less fit solutions ensure genetic diversity within the genetic pool of the parents and therefore ensure the genetic diversity of the subsequent generation of children.

Opinion is divided over the importance of crossover versus mutation. There are many references in Fogel (2006) that support the importance of mutation-based search.

Although crossover and mutation are known as the main genetic operators, it is possible to use other operators such as regrouping, colonization-extinction, or migration in genetic algorithms.

It is worth tuning parameters such as the mutation probability, crossover probability and population size to find reasonable settings for the problem's complexity class being worked on. A very small mutation rate may lead to genetic drift (which is non-ergodic in nature). A recombination rate that is too high may lead to premature convergence of the genetic algorithm. A mutation rate that is too high may lead to loss of good solutions, unless elitist selection is employed. An adequate population size ensures sufficient genetic diversity for the problem at hand, but can lead to a waste of computational resources if set to a value larger than required.

Basic outline of Genetic Algorithm

Figure 1 shows the various steps involved in Genetic Algorithm process.

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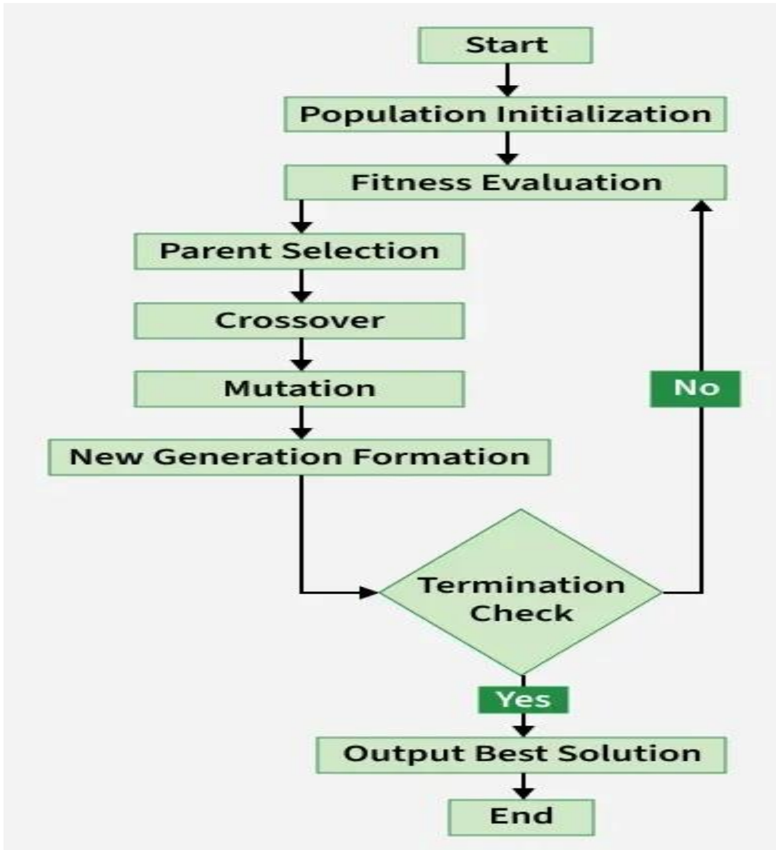

Fig.1 Flowchart showing the Genetic Algorithm process.

IV. Results & Discussion

MATLAB Implementation

GAs procedure is implemented on MATLAB software. A model is programmed in MATLAB using genetic algorithm for optimization of construction project scheduling. Problem solving model in MATLAB requires the relevant data that is activity, predecessors, resource availability and resources requirements per day. Performing Optimization Process This application is perform to optimize the process of the resource allocation and levelling on the construction project having 20 activities and for ease we took only one type resource for allocation and levelling. Optimization options are set as follows- Options of GA Population Size: number of the population.

Crossover Fraction: Fraction of the population that is not mutated.

Stopping conditions: as GA gives results that shows no further improvements. Implementing the proposed GA procedure on software simplifies the implementation process and provides project managers with an automated tool to improve the results of their familiar software.

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In this study MATLAB software is selected for implementing the GA procedure, for the reasons mentioned earlier as well as its ease of use and programmability features. The detailed GA procedure is shown in figure 5.1

An implementation of genetic algorithm developed a model for optimisation of construction project scheduling using MATLAB software. The practitioners' software provides powerful capabilities to apply GA for optimisation. It is hoped that implementation of this model justified the efforts spent in proper planning and scheduling as key to effective construction project management and ultimately to actual saving in project time and cost.GA can be utilized in the other areas of project management such as productivity, value engineering etc

Analysis

- Activity=5
- Activity duration= 10 20 30 40 50
- Labour Cost=1000 1200 1500 1800 2000
- Labour =10
- Population Size =50
- Generation=100

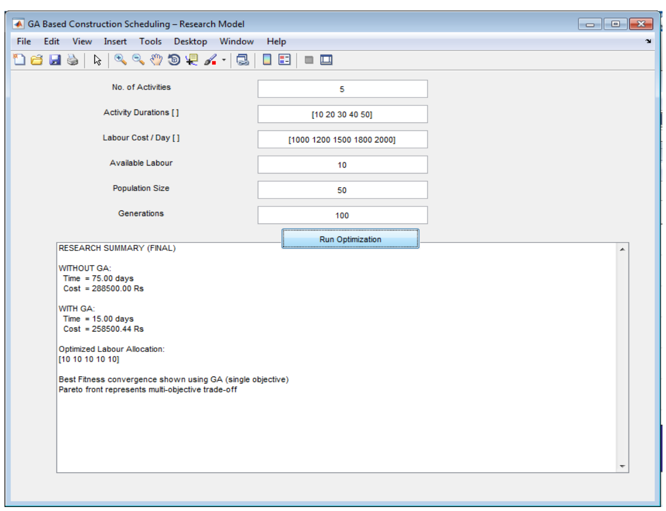

Fig.4.1 GA algorithm.

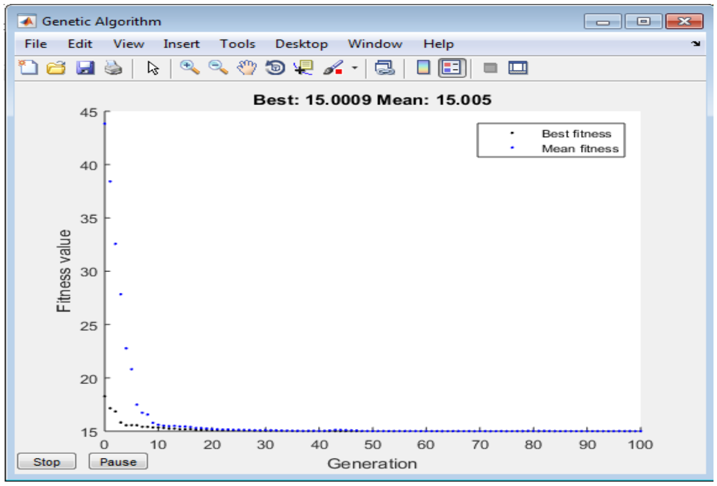

Fig.4.2 Best Fit Value.

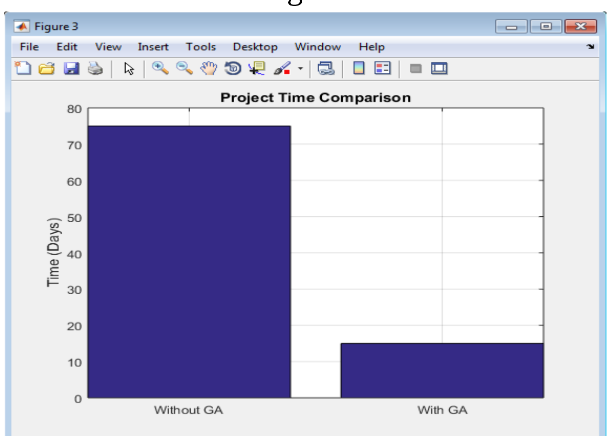

Fig.4.3 Project time Comparison.

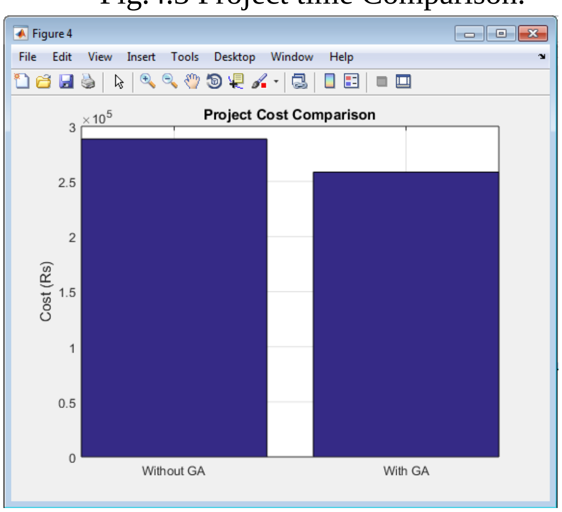

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Fig.4.4 Project Cost Comparison.

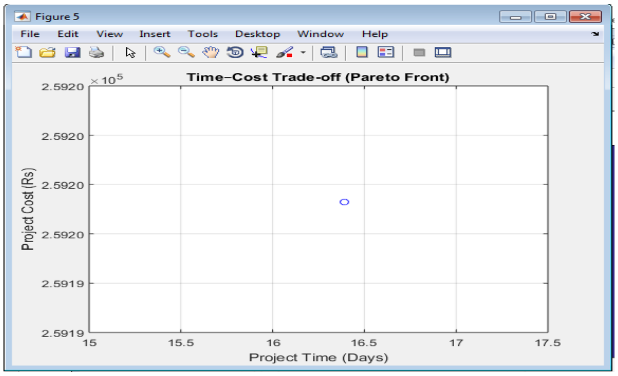

Fig.4.5 Trade off.

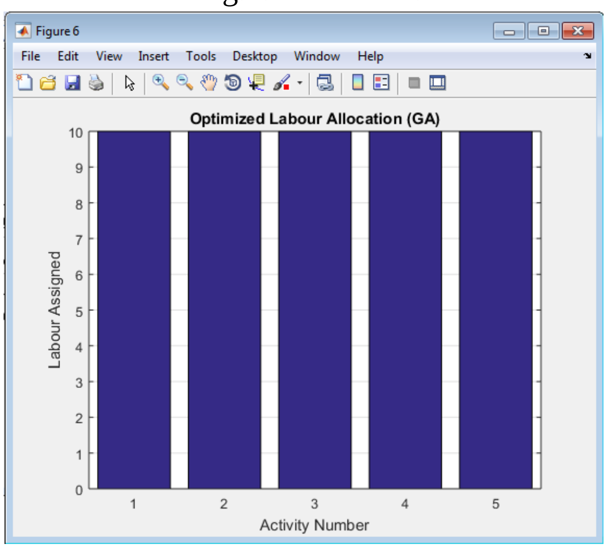

Fig.4.6 Labour Assigning.

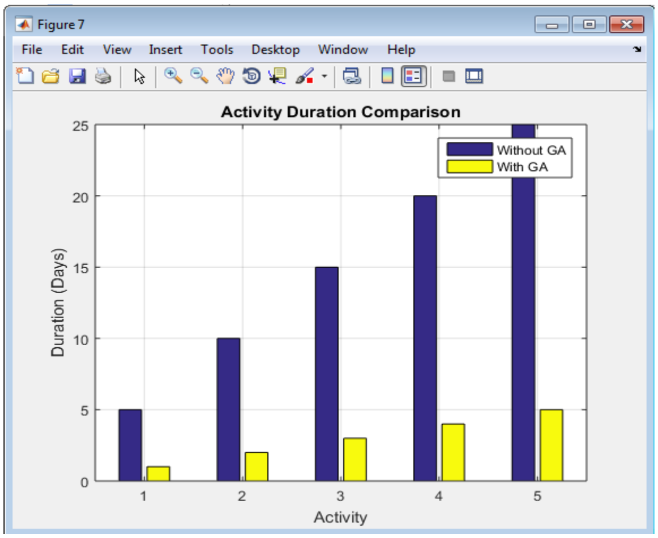

Fig.4.7 Activity Duration.

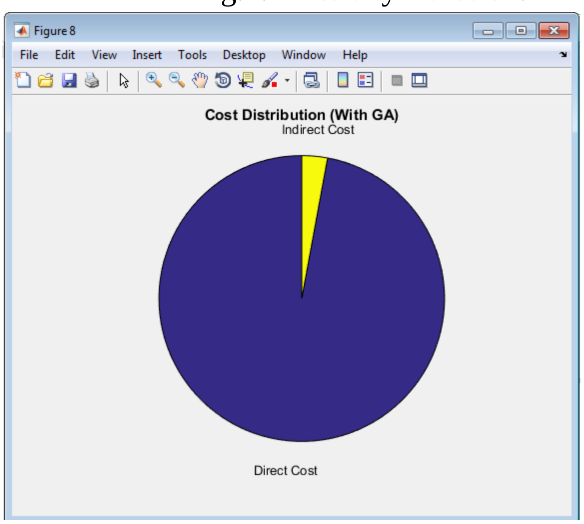

Fig.4.8 Pi chart Direct and indirect chart.

Activity Increasing

- Activity=10
- Activity duration= [10 20 30 40 50 5 10 15 40 20]
- Labour Cost= [1000 1200 1500 1800 2000 25000 10000 1000 2000 3000]
- Labour =20
- Population Size =50
- Generation=100

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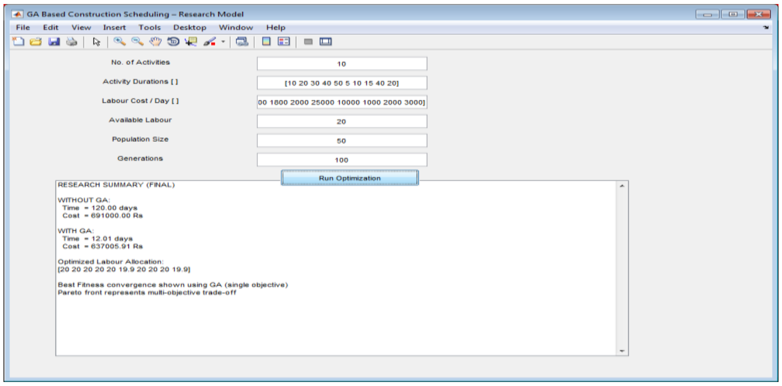

Fig.4.9 Activity 10 And Labour 20 GA Analysis.

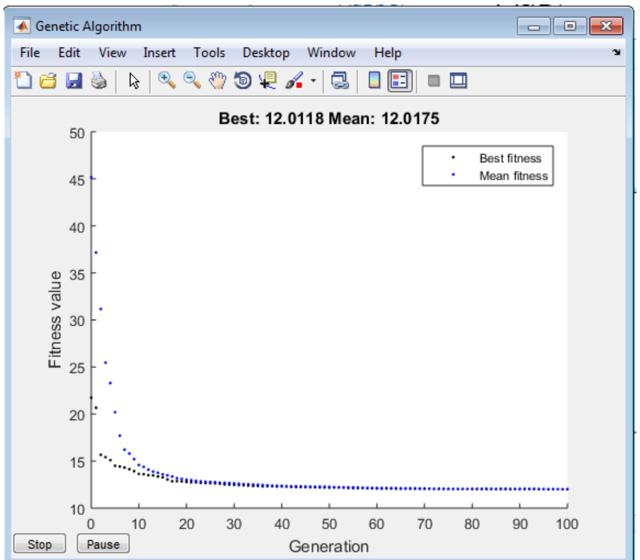

Fig.4.10 Activity 10 And Labour 20 Best Fit.

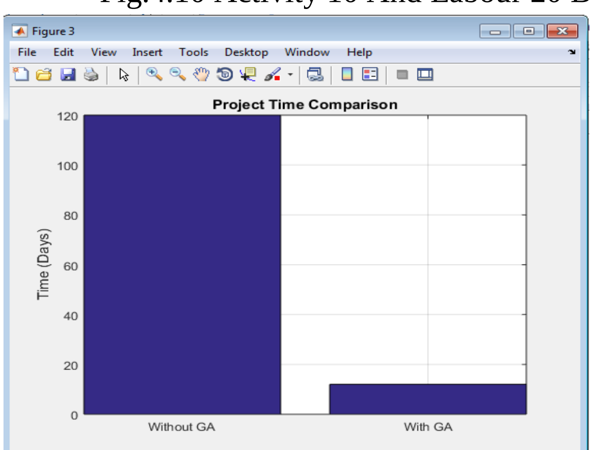

Fig.4.11 Activity 10 And Labour 20 With and Without GA Time.

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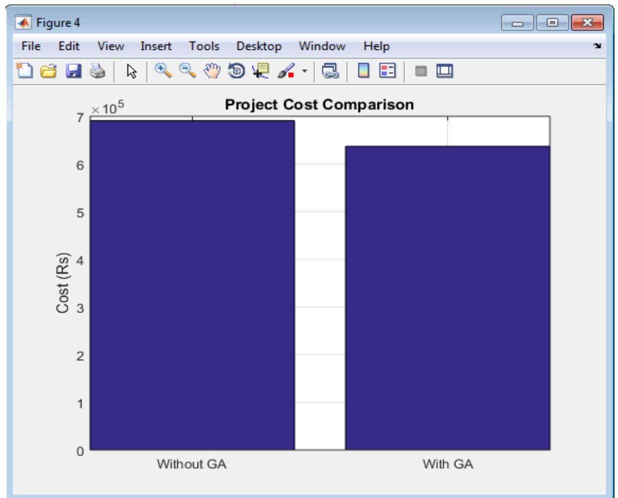

Fig.4.12 Activity 10 And Labour 20 With and Without GA Cost.

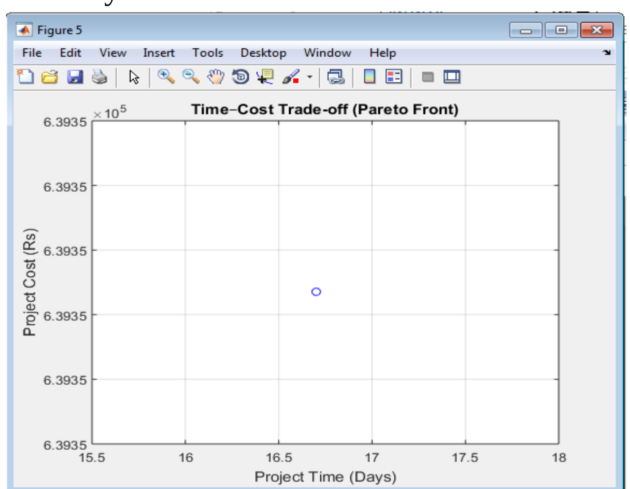

Fig.4.13 Trade off.

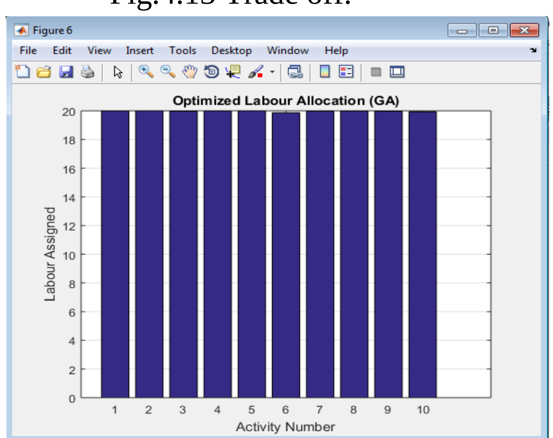

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Fig.4.14 Activity 10 And Labour 20 Labour Assigned.

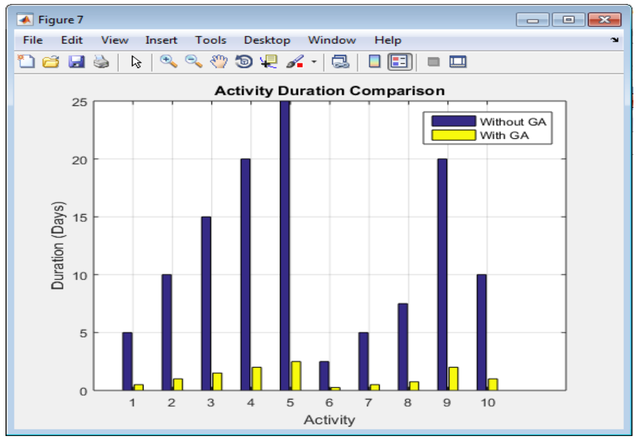

Fig.4.15 Activity 10 And Labour 20 Duration.

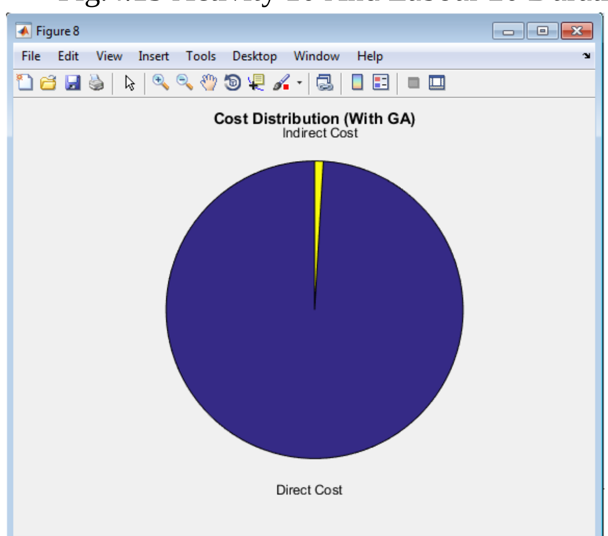

Fig.4.16 Activity 10 And Labour 20 Direct and Indirect Cost.

V.CONCLUSION AND FUTURE SCOPE

Conclusion

The research demonstrates the effectiveness of Genetic Algorithm (GA) in optimizing construction project schedules, considering both project duration and cost. By allocating available labour optimally across different activities, the GA-based approach significantly reduces overall project time compared to conventional scheduling methods, as illustrated by the Gantt charts. Moreover, incorporating a realistic cost model that includes both direct labour costs and indirect time-dependent overheads allows the algorithm to achieve a true time–cost trade-off, which is validated through the Pareto front analysis. The comparison of “With GA” and

"Without GA" schedules clearly shows that the optimized approach not only shortens the project duration but also minimizes total project costs. Additional graphical analyses, including activity-wise duration reduction, labour allocation, and cost breakdown, provide deeper insights into resource utilization and cost efficiency. Overall, the study confirms that GA-based multi-objective optimization is a powerful and practical tool for improving construction project performance, offering a systematic methodology for project managers to balance time and cost efficiently, which can be directly applied in real-world scenarios or integrated with software like MATLAB for enhanced planning and decision-making.

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