IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 4 September 2023, accepted 14 September 2023, date of publication 19 September 2023, date of current version 7 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3317137

RESEARCH ARTICLE

Building a Genetic Algorithm-Based and BIM-Based 5D Time and Cost Optimization Model

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This work was funded by the Deanship of Graduate Studies and Scientific Research at Jouf University under grant No (DSR2023-02-02040).

ABSTRACT The digitalization of data has recently had an impact on the building industry. Building information modeling (BIM) is a highly developed technology that is used to predict the cost, lifespan, energy use, and efficiency of buildings. To enhance the BIM accuracy of cost and time estimation currently, it's easier than before by Using evolutionary algorithms (EA), which include contemporary algorithms like evolutionary strategies (ES), evolutionary programming (EP), particle swarm optimization (PSO), differential evolution (DE), and genetic algorithms (GA), the integration of artificial intelligence (AI). This study uses a code (plugin) created by GA and integrated into the BIM-5D model via Navisworks as a plugin to reduce the overall time and cost of construction projects. The plugin code, developed with Microsoft Visual Studio and the C# programming language, is an interface that enhances the accuracy of time and cost during construction stages with various five project time scenarios. The study's findings indicate that the suggested plugin reduces project time by roughly 20% while also saving various amounts of money.

INDEX TERMS Artificial intelligence (AI), building information modeling (BIM), cash flow, critical path method (CPM), time and cost optimization.

I. INTRODUCTION

One of the most important aspects of construction project management, after scheduling and planning, is determining the cash flow of the project. Cash flow refers to cash expenditures, known as cash outflow, and cash revenues, known as cash inflow, during a project's lifespan [1]. Forecasting cash flow involves projecting cash inflows and outflows over the project's entire life cycle. Cash flow diagrams are essential tools for efficiently managing a project's finances by illustrating its cash flow profile over time [2]. They show the cash inflow and outflow profiles, with the net cash flow represented by the difference between them. Fig. 1 illustrates the cash-out Profile, a curve depicting the expected progress and cumulative cash-out values of the contractor throughout the project's duration [3], [4]. The cash-in profile, on the other hand, is represented by a stepped curve related to the contract type and shows the owner's expected monthly payments to the contractor. The cash-out profile, on the other hand, is represented by a straight line. A positive net cash flow indicates a cash surplus, while a negative net cash flow indicates a cash deficit that requires external financing to cover. To cover mobilization expenses and ease the financial burden on the contractor during the mobilization and initiation phase of construction works, the contractor should request a down payment at the project's outset [5], [6].

Scheduling and planning play crucial roles in creating a cash flow prediction model.

Construction planning is a crucial and demanding task in managing and executing construction projects [7], [8]. It involves various activities, such as selecting appropriate technology, delineating work requirements, estimating necessary resources, determining task completion time, and identifying interactions among different work components.

The associate editor coordinating the review of this manuscript and approving it for publication was Ines Domingues.

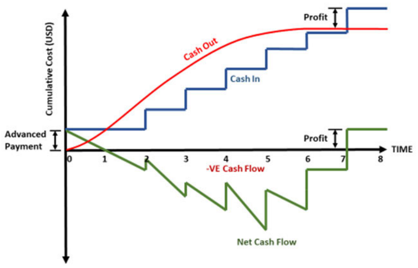

FIGURE 1. Illustrates the diagrams for cash flow and net cash flow [Ismail M. Basha, Ahmed H. Ibrahim, Ahmed N. Abd El-Azim].

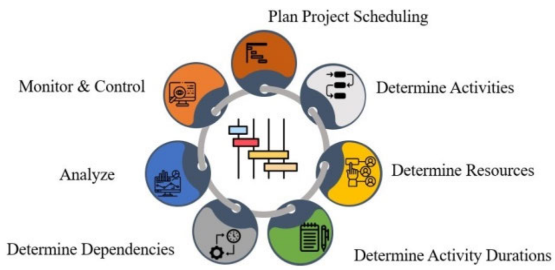

FIGURE 2. Benefits of Scheduling in Construction [Zayed, T., & Liu, Y].

The ultimate goal is to develop a comprehensive plan that effectively manages the budget and schedules work [9], [10]. The planner's primary responsibility is to provide a framework for budget, work schedule, and communication among work parties. Project planning involves establishing a predetermined course of action for an anticipated environment [11]. According to the Project Management Institute, the planning process involves defining and refining project objectives and selecting the best alternatives to achieve them [12]. The planning function creates and controls project schedules and determines materials, human resources, equipment, and supplies needed for each task. It also involves documenting the relationships between all project activities and examining activity sequences, durations, resource requirements, and scheduling constraints to create a project schedule model. Monitoring and controlling involves comparing actual and planned dates, durations, resource quantities, and performance metrics. Planners must focus on task organization for successful project management, as shown in Fig. 2. Construction planning considers the various parts of a project and its circumstances based on cost or schedule in collaboration with available resources, or both, to complete the project.

In project scheduling, planners aim to minimize the time and cost needed to finish a project, which can be achieved by utilizing optimization techniques for both time and cost.

The cost of a project involves both direct and indirect expenses associated with its activities. Planners can shorten project duration by conducting a "time-cost trade-off analysis" [13]. The purpose of this analysis is to identify the time-cost options that will result in the best schedule within the given parameters. Fig. 3 illustrates the relationship between time and cost, indicating that as project duration increases, direct costs decrease while indirect or overhead

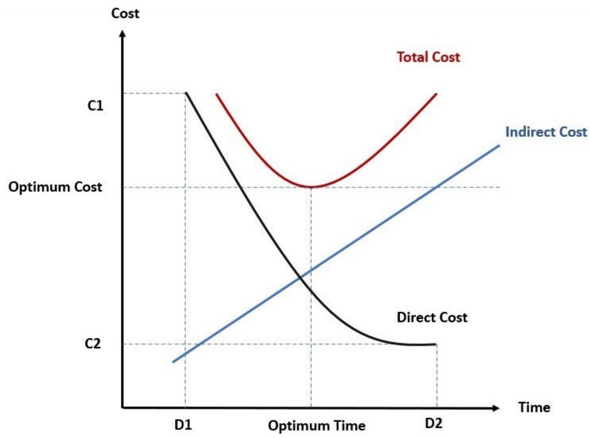

FIGURE 3. Relationship between time and cost [N. K. Park and Y. An].

costs rise. The optimal combination of time and cost yields the best project duration and cost.

Thus, this research aims to optimize the overall time and cost stages of construction projects through five different project time scenarios. To achieve this objective, the research presents a proposal for integrating a GA model into the BIM-5D model interface. The proposed model utilizes a spreadsheet program and is implemented via the Navisworks plugin by coding all tasks using the C# programming language through the Navisworks Application Programming Interface (API). Finally, the results of this study and comparisons will be presented through Power-BI dashboards.

II. LITERATURE REVIEW

Construction projects involve various activities, including planning, design, execution, management, and, sometimes, repair, which are carried out by different disciplines, such as architecture, civil, electrical, and mechanical, throughout the project's lifecycle. To determine the project's overall duration and budget, it is crucial to consider the time and budget of each activity. Effective financial resource management is crucial for construction firms [14], and among the numerous tasks involved, effective cash flow management holds the utmost significance [15]. Inadequate management of financial resources, coupled with cash flow issues, can lead to significant disruptions in construction projects and, in some instances, even result in contractor bankruptcies [2], [16]. Thus, contractors must make precise cash flow projections throughout project life cycles [17], [18], including forecasting, planning, monitoring, and controlling cash inflows and outflows. Since cash is widely regarded as the most valuable resource within construction firms, cash flow management should be a top priority for managers [19]. The primary reason for construction company failures is often the absence of sufficient funds to support daily operations [2], [20]. Therefore, having a solid understanding of the actual cash flow requirements throughout the construction phases is essential [21]. Similarly, Duran (2017) [64] noted that numerous projects are not completed on time, giving the construction sector a bad image for completing projects on time, and project managers are often held accountable for this [22]. Effective time management is essential for organizing and executing plans to complete tasks within a suitable duration. It is crucial for fulfilling budgets, achieving program objectives, and generating profits. Contractors must prioritize effective planning and scheduling to achieve successful project implementation and gain a competitive edge in bidding, on-time delivery, and customization [23]. Planning involves identifying necessary resources and gathering detailed information, while scheduling requires skillful allocation of operations using available resources to optimize pre-defined goals [24]. The Critical Path Method (CPM), a widely used scheduling technique in construction project management, provides vital information for effectively managing projects and serves as the foundation for analyzing the impact of construction process delays [25], [26]. Balancing quality, time, and cost is a crucial trade-off in project planning. Construction management engineers aim to determine the optimal point between time and cost by using trade-off rates [27]. Due to the complexity and rapid development of the business, there is a growing need for sophisticated building methods and models that can address complex challenges. Thanks to powerful technology and software, BIM and optimization technologies have become essential for improving construction planning, scheduling, and resource management. In the early 2000s, BIM was established as an information model for building components [28]. BIM has been proposed as an effective platform for enhancing collaboration among construction sectors, management teams, and owners through the integration of related data and information for project participants [29], [30]. BIM facilitates the life cycle management of construction, which includes primary project assessment, scheduling, design, construction (equipment installation, budget control, and process management), operation management, maintenance, modification, and demolition processes [31], [32]. The addition of time and cost to the BIM model creates the fourth and fifth dimensions, enabling project schedules and cost estimates to be improved during the early stages of design [33]. The apparent benefits of BIM in addressing the technical complexity of a construction project have resulted in its widespread usage as a tool to increase construction management efficiency. Recently, a strategy for optimizing BIM capabilities based on artificial intelligence has been proposed, enabling researchers to create and utilize a BIM-based strategy for optimizing traditional building methods [34]. On the other hand, artificial intelligence encompasses various technologies that enable sophisticated computers to utilize human intelligence and skills through listening, understanding, acting, and learning, which allows humans to achieve higher performance and outcomes than ever before [35]. BIM collects data on crucial areas like design, planning, schedule, safety, quality, and budget, which can be analyzed through robust AI algorithms to optimize them [36].

Engineering applications and scientific research frequently encounter optimization problems that require finding the optimal solution or solutions for a specific problem [37]. Boyd and Vandenberghe define optimization problems as the process of identifying the best solution among various options. The 1950s marked the advent of artificial intelligence, which led to the invention of evolutionary algorithms (EA), a new branch of the metaheuristic algorithm family [38]. Genetic algorithms (GA) are among the latest EA family algorithms, and they have emerged as a powerful tool for finding optimal solutions to intricate engineering optimization problems (EOPs) over the past few decades [39], [40], [41], and [42]. GA mimics genetics and natural selection by replicating reproduction, mating, and mutation. It randomly selects individuals and creates a new set of individuals adapted to their environment through crossover and mutation, which enables the population to progress towards better regions of the overall search space. Genetic algorithms are innovative global optimization techniques widely used in function optimization, combinatorial optimization, production scheduling, and other areas [43].

In another way, the applications of the algorithms in the industry are very common as mentioned by [44] that deal with the optimization of meat and poultry farm inventory stock using data analytics for green supply chain networks in two folds. In the first step, a traceability method with the IOT-based system for demand-supply monitoring. The second step: includes optimization of the supply network to reduce the carbon emissions from transportation. Another application in civil engineering has been illustrated by [45], A bridge-type compliant mechanism is discussed, and the components of this mechanism like design dimensions, design dimensions of the flexure joint, linked size on the displacement, and stress of the bridge-type compliant mechanism are analyzed based on the FEA by ANSYS. S/N evaluation, ANOVA, RE, and surface plots are also used as aids in the design problems.

For all the above, the primary objective of this study is to improve the efficiency of construction projects in terms of their overall duration (with five different scenarios of project time) and expenses. To achieve this aim, the research proposes the integration of a GA model into the BIM-5D model interface. This proposed model employs a spreadsheet program and is executed via the Navisworks plugin. The implementation involves coding all tasks using the C# programming language through the Navisworks Application Programming Interface (API). In conclusion, the study's findings and relevant comparisons will be presented using Power BI dashboards. The basic steps of this research outline are categorized as follows: (1) introduction, (2) reviewing the literature and assessing needs, (3) BIM & Genetic Algorithm, (4) research methodology, (5) validation of the GA-API model, (6) case study, (7) results and discussion, and (8) conclusion and future work.

III. BIM 5D & GENETIC ALGORITHM (GA)

BIM is a process that improves project quality, communication, and management while reducing costs and improving schedules [45]. The digital building of a three-dimensional model, including both graphical and non-graphical information, is the third dimension of BIM [46]. The BIM 3D application helps primary contractors optimize the allocation of space for facilities, equipment, and material storage areas [47]. The scheduling component, which is the fourth feature of BIM, is used to analyze and examine the evolution of the project [47]. A 4D BIM is primarily associated with time, planning, and scheduling, according to academics and practitioners [48]. Integrating all cost-related information, including quantity, schedules, and pricing, 5D BIM is beneficial during both the early design stage and the construction phase, where changes are likely to occur [49]. BIM enhances communication among various teams and professionals, streamlines interdisciplinary work, and offers a comprehensive overview of the project, as illustrated in Fig. 4. The model stores information about every component of the building, clarifies clashes, avoids conflicts with contradictory information between documents and building systems, and reduces rework and modifications [50].

Commercial information about products can be added and provided on suppliers' websites. The information provided in the model enables the program to directly assess the building's energy and environmental performance. BIM saves time as documents are automatically generated, linked, and updated from the model, allowing more time for design and decision-making. The efficiency of team members and working time ensures more profit on the investment and positive returns. According to the McGrew Hill Construction Report, over 50% of firms view offering BIM to their clients as an advantage for gaining projects. Almost every developed country has or is developing legislation mandating the use of BIM for at least publicly funded projects.

Integrating BIM with AI technology can offer numerous opportunities for building and designing. The terms digitization and digital transformation are often used interchangeably, but they represent different levels of digital advancement. Digitization involves converting analog information into a digital format, such as using a phone app for checklists instead of paper. Digitalization refers to the point at which machines can perform tasks that were previously under human control, meaning their responses are comparable to human actions like decision-making and updating.

Digital transformation involves using digital technologies to fundamentally transform the way an organization operates [51]. The construction industry, as shown in Fig. 5, may benefit from AI in dealing with its most significant issues, such as costs, schedules, and safety [52]. However, the industry is still in the early stages of its digital transformation, with AI yet to be used in many projects. The successful implementation of the plan will depend on how well humans and AI work together. AI has several advantages for construction projects,

FIGURE 4. Benefits of BIM in construction.

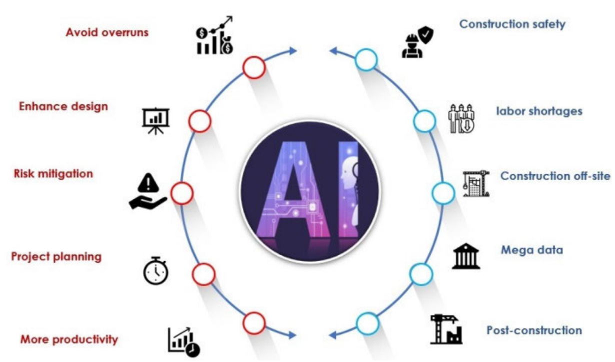

FIGURE 5. Benefits of AI in construction.

such as providing remote access to real-world training materials to enhance employee skills and knowledge, reducing project onboarding time, and using generative design to identify and fix model clashes.

General contractors also use AI and machine learning to monitor and rank job site risks, allowing the project team to focus on the most important ones. Reinforcement learning enables algorithms to learn from their mistakes, improving project planning over time by comparing an infinite number of project combinations and alternatives. Self-driving construction equipment is better than humans at tasks such as pouring concrete, laying bricks, welding, and demolishing buildings. Advanced analytics and AI-powered algorithms provide information on how buildings, bridges, roads, and other structures work and their efficiency. Today, data from various sources, including mobile device images, security sensors, drone footage, and BIM, are collected. Machines working by themselves can put together structures like walls faster than humans on a production line. Companies in the construction industry are starting to use AI and machine learning to improve their operations.

To grasp the current state of AI in the construction industry, it's important to understand the major subfields of AI. These subfields have emerged due to the progress in AI applications, including optimization. Therefore, this section provides an overview of AI optimization techniques. Optimization involves making decisions that produce optimal results within

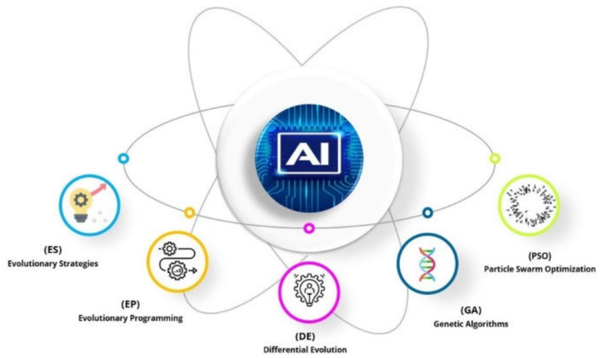

FIGURE 6. Artificially intelligent optimization methods.

a given set of constraints [53]. Throughout one's life, optimization focuses on finding the best solution to any problem. Evolutionary Algorithms (EA), a new type of metaheuristic algorithm [53], emerged with the development of artificial intelligence in the 1950s. Notable EA algorithms include evolutionary programming (EP), genetic algorithms (GA), particle swarm optimization (PSO), evolutionary strategies (ES), and differential evolution (DE) [53]. Fig. 6 illustrates the five most common AI optimization strategies. Evolutionary strategies (ES) are a subtype of nature-inspired direct search and optimization processes that use mutation, recombination, and selection to develop progressively improved solutions within a population.

Evolutionary programming and differential evolution are two essential evolutionary algorithm paradigms. Metaheuristics, such as differential evolution and particle swarm optimization, search large candidate solution spaces without making any assumptions about the problem being optimized. However, they do not guarantee optimal results. Genetic algorithms, on the other hand, utilize natural genetics-based techniques for global search and optimization. They simultaneously combine multiple potential solutions and investigate the search space [54]. Genetic algorithms, also known as GA, offer a solution to optimize a population of candidates toward better options [55]. This approach is useful for solving optimization problems, such as scheduling and shortest path, as well as in modeling and simulation, where random functions are applied [56].

In GA, solutions evolve like in nature through hereditary gene crossover and mutation, as shown in Fig. 7. These solutions are called chromosomes, and each contains numerous genes with values for the problem's decision variables expressed in binary or real numbers. The number of decision variables is equal to the length of the chromosomes [57]. A genetic algorithm proceeds through the following stages:

Initial Population:

The initial group to be included in this process is referred to as the "population." Each person presents a potential solution to the problem being addressed. Genes are variables that determine an individual's characteristics and attributes, and they are present in chromosomes composed of DNA, as illustrated in Fig. 8.

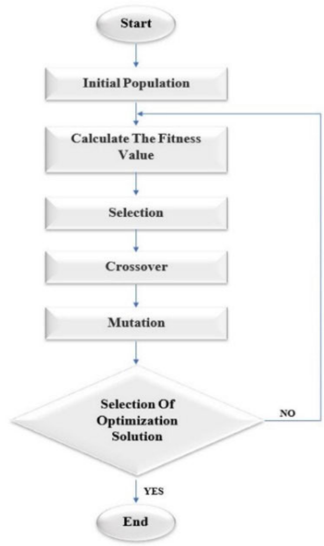

FIGURE 7. Genetic algorithm process [56].

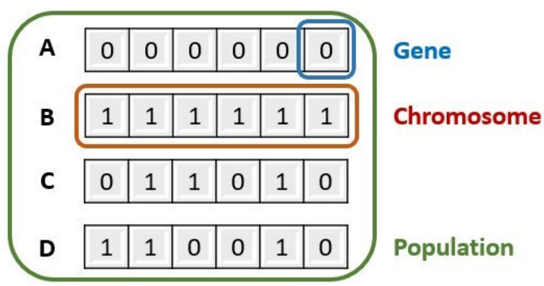

FIGURE 8. Gene, population, and chromosomes.

Fitness Function:

The fitness function assesses a person's ability to compete with others for a particular position. A fitness level is assigned to each user, and those with a higher level have a better chance of having children.

Selection:

The selection phase aims to identify physically fit individuals who can pass on their genes to the next generations. Two couples with superior physical fitness have been chosen for this purpose. Those with higher fitness levels are more likely to be selected for reproduction, as it is associated with higher reproductive success.

Crossover:

In a genetic algorithm, the crossover process plays a crucial role. It involves selecting a random crossover point from the genes of each set of parents that will mate to produce offspring, as illustrated in Fig. 9.

Mutation:

Certain genes may have a low probability of being altered in new offspring through mutation. This means that some of the bits in the string can be reversed, as shown in Fig. 10.

The phases are repeated in sequence to improve the quality of individuals in each new generation. The algorithm ends if the population has reached convergence, meaning that the

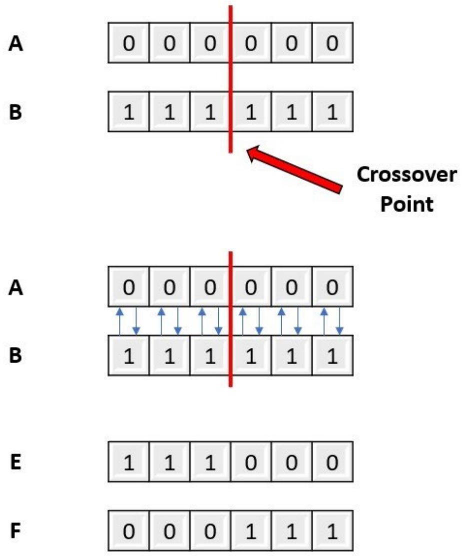

FIGURE 9. Crossover, exchange, and new offspring.

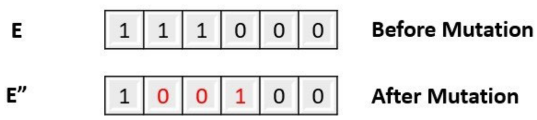

FIGURE 10. Before and after Mutation.

offspring are not significantly different from their parents. Once the genetic algorithm has generated a set of solutions for the problem, we can consider it resolved because it has produced a set of keys.

IV. METHODOLOGY OF THE RESEARCH

To optimize the cost and time of construction projects, the study recommends integrating the 5D BIM interface-based framework and the GA model. The process consists of four stages, each with input data, the model with its dimension, and output data, as depicted in Fig. 11. In Stage One, the input data includes the bill of quantities, project code, and project description to create a 3D BIM model. The output data of this stage are quantity take-off (QTO) and extractions, which can also be referred to as the Initialization of Construction data. In Stage Two, the input data includes adding productivity (labor, equipment) to the previous stage to create a 4D BIM model. The output data at this stage are schedule data and integration of the QTO list. The third stage introduces the 5D BIM model cost database by adding the cost database (equipment, man-hours, materials, and overhead costs) as input data. The output of this stage is the integration data between cost data, schedule data, and the QTO list. In the fourth stage, the input data includes the expected five scenarios of the project time. This creates a 5D BIM model with a GA algorithm, which is the core of the research to find the optimal solution related to time and cost.

In terms of methodology and research design, the study follows the recommended procedure for developing and

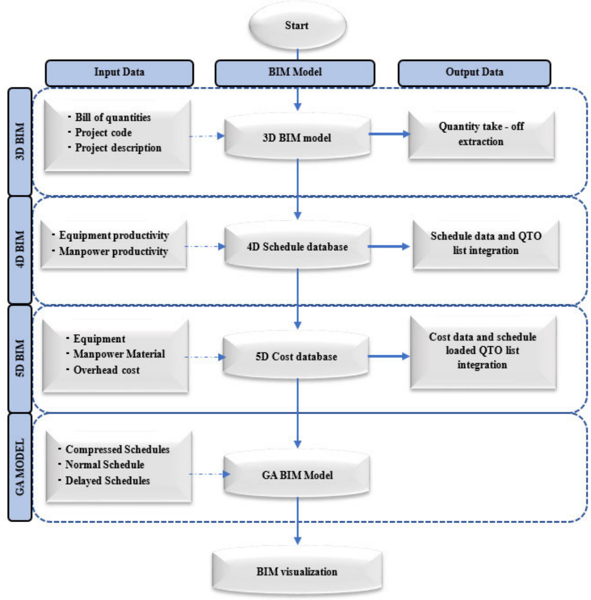

FIGURE 11. Process flow diagram of optimization.

evaluating a proof of concept for the new structure, as seen in prior BIM studies [58, and 59]. Various tools and techniques are utilized in the analytical portion of this study, including cash flow estimation, critical path method (CPM) estimation, building information modeling in five dimensions (5D) using BIM, Power BI dashboards, and a GA optimization model implemented using Microsoft Visual Studio (MS) with the C# programming language acting as an application programming interface (API) within Navisworks.

Once the 3D model is constructed, it is imported into Navisworks to enhance the 4D and 5D evaluations. This includes customization of the quantities takeoff (QTO) rules to match the total cost price list name standard and the inclusion of level information in the description. This enables an Excel query to connect the databases for the QTO, price list, and Gantt chart, and export the QTO report to Excel. The result is a Gantt chart displaying the total cost of each activity. Fig. 12 demonstrates the use of Excel to achieve compatibility with Primavera P6.

BIM technology is used to import the Gantt chart with the entire cost to clarify and organize execution scheduling, and create 4D and 5D simulations.

Integrating schedule data and the QTO list, which contains resource information from the BIM model, into the external schedule database for project schedule computation, is a crucial step. The schedule database includes equipment and labor productivity, which are utilized to calculate the duration of each work item linked to the QTO list. By manually adding the logistic sequence between separate tasks, a schedule-loaded QTO list is generated. The concept of 5D BIM, as depicted in Fig. 13, involves the integration of a 3D model, 4D scheduling, and 5D cost for effective project management. The BIM model is continuously updated, providing

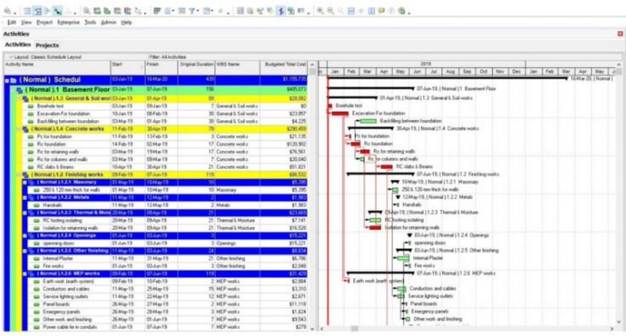

FIGURE 12. Scenario of a normal project duration and its schedule.

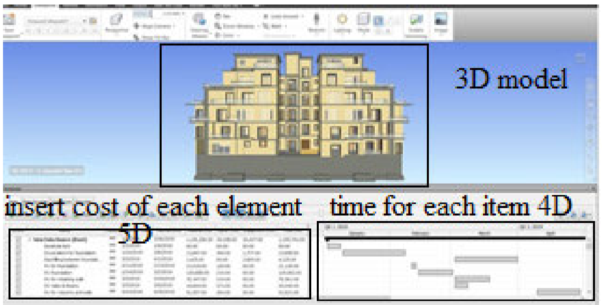

FIGURE 13. 5D BIM model.

construction management with timely information on the project's duration and cost. The system also generates a resource catalog that considers the equipment, supplies, and team members required for successful project execution. This process includes merging the QTO list, loaded with scheduling data, with an external database that encompasses labor, material, and equipment costs.

Additionally, it is necessary to include other indirect costs such as supervision, cleanup fees, bonds, or insurance, which cannot be directly linked to a specific building component. Once this estimation is complete, the timeline file can be updated with cost information and used to generate a 5D BIM model through a 5D software platform, enabling 5D simulation. Subsequently, the genetic algorithm stage is divided into two steps, which are as follows:

A. INITIAL DATASET ESTIMATION

The construction tasks for the project have been identified, and their interrelationships have been outlined. The duration of each task is determined by its time and cost in creation units, and the length of the activity is denoted by a chromosomal character. The activity periods are divided into five scenarios, including two compressed periods, one ordinary period, and two delayed periods. Choosing these five scenarios is the most appropriate option as they closely resemble the actual expected cases. Five scenarios are a suitable number because exceeding this number would slow down the program while reducing it to less than five would result in decreased accuracy due to limited diversity in activities. Each choice period (two compressed, one normal, and two delayed) is based on recommendations from seasoned engineers.

B. ANALYSIS OF THE GENETIC ALGORITHM (GA) MODEL

A Genetic Algorithm (GA) is utilized to determine the optimal approach for completing project activities within a given timeframe and budget. The scope of this study involves the creation of a simple GA that focuses on time-cost optimization, as well as the development of a BIM model for GA, as depicted in Fig. 14.

The procedure for the genetic algorithm is outlined below:

1) To begin, the design space is populated with a random selection of chromosomes, referred to as the "parent population." This serves as the initial generation, as depicted in Fig. 15, and encompasses all activities of our project. Each activity is represented by five instances: the first indicating its normal state, followed by two instances for delays of one and two days respectively, and two more for compression of one and two days each.

2) After randomly selecting chromosomes to represent each unique activity type (normal, delayed, or compressed) from our design space, individuals are created. These individuals are then assigned a score based on the value of their fitness function, as illustrated in Fig. 16.

3) To obtain the correct order of activities, the chromosomes (activities) for each individual are rearranged using the critical path method. Subsequently, the duration is calculated as a fitness score for all individuals. The populations are then sorted based on the fitness score, as demonstrated in Fig. 17. In each iteration, a total of 100 individuals are created and sorted based on their fitness score, which is determined by the minimum duration to the maximum.

4) The following genetic operators (mating) are employed: reproduction, which involves reproducing a fit individual; crossover, which involves exchanging portions of two fit individuals to produce offspring; and mutation, which involves applying a random perturbation to components of an individual. The occurrence of each of these operators is determined by chance, as depicted in Fig. 18. To create the new generation, the 100 individuals are divided in half, and the 50 with the lowest fitness ratings are eliminated. The remaining 50 individuals are then paired with the ten best individuals to create 90 individuals for the next generation. Consequently, the new generation consists of 100 individuals, and mating is carried out by selecting genes from either person one or person two (selected from the first 50 individuals) or from mutation (any gene or gene activity from the entire original space). In our case, the mutation occurs at a modest known ratio of 10%.

5) Mating of the genes is continued until convergence is achieved, at which point the operation is terminated. Convergence is attained when the previously specified consistency number is reached. For instance, if the number of iterations reaches 500, the program will simply exit and use the final fitness score. It is important to note that all of these steps are carried out in a single runtime.

6) To find the optimum run that yields the best or shortest duration, we repeat the previous stages by running our

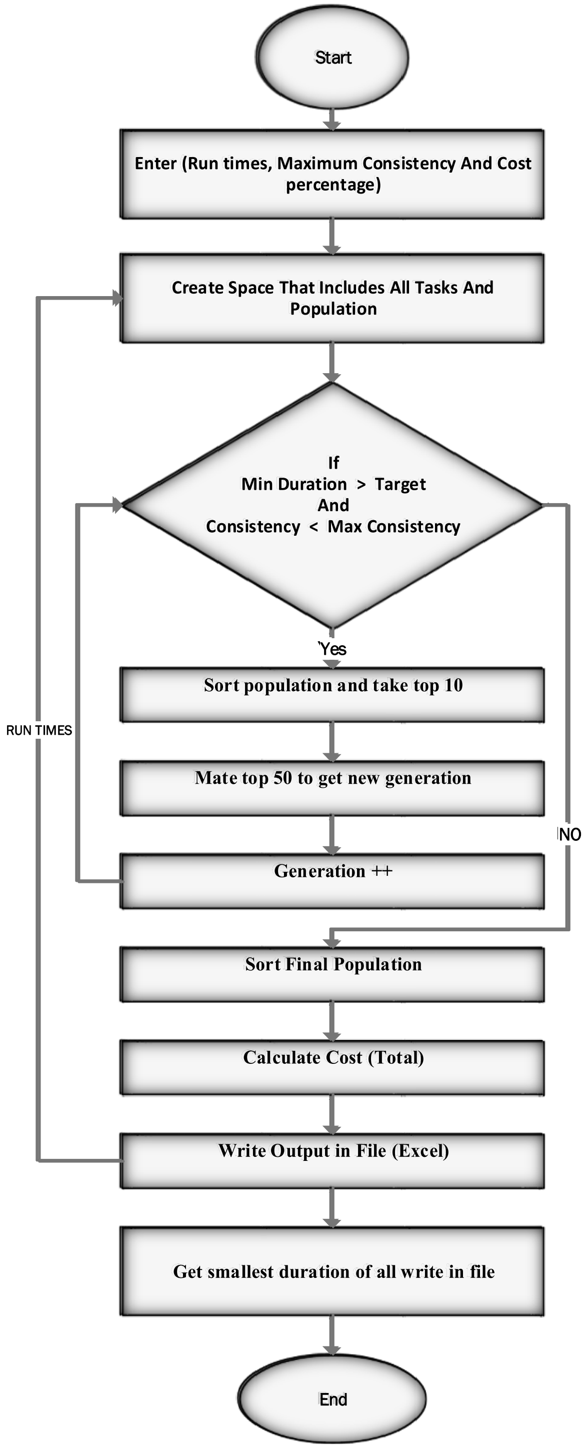

FIGURE 14. Flow Chart of the proposed GA-API BIM model.

program multiple times. We utilize the runtime parameter as explained earlier in the process.

In the final step, we need to verify and obtain the best result based on the duration of the project while ensuring that the cost does not exceed the percentage specified at the outset. All results are then outputted into an Excel sheet. The number of output files is determined by the number of run times entered at the beginning.

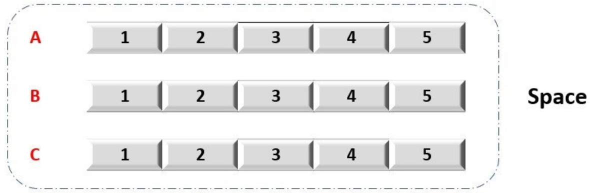

FIGURE 15. The initial generation.

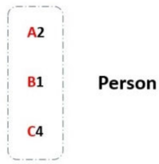

FIGURE 16. Score of the initial generation.

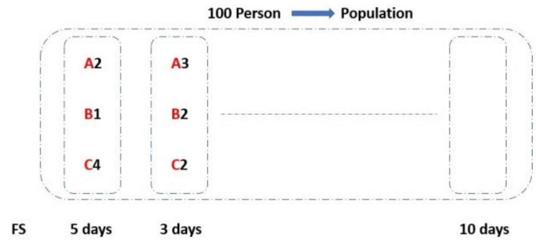

FIGURE 17. Create 100 random persons.

Fig. 19 illustrates the first three inputs of the API GA model.

"Run Times" involves running the model multiple times, resulting in different outcomes with each iteration until the optimal solution is reached. This iterative process allows the model to refine its results, and after extensive repetition, the optimal runtime occurs after 200 iterations.

"Maximum Consistency" pertains to the total number of times the model will run, even after obtaining the optimal solution. Without a limit, the model would continue running indefinitely, without further optimization. To prevent this, determine and set the maximum consistency to 500 in this application. After reaching 500 iterations, the optimization process, optimal learning, and performance are completed.

The "Cost Percentage" refers to the maximum percentage of cost reduction aims to achieve while minimizing project duration. It signifies the threshold that can't be exceeded in terms of cost reduction when prioritizing the reduction of project duration. The research deals with the approach in two ways. The first one focuses on minimizing project duration, which is a primary objective. The main aim is to minimize the duration as much as possible without incurring significant cost increases. This optimization prioritizes duration reduction. Once achieving the minimum duration, repeating the GA process to further optimize cost reduction must be done. The target of this is to control costs and prevent excessive increases while also aiming for maximum duration reduction. The "Cost Percentage" parameter helps to strike

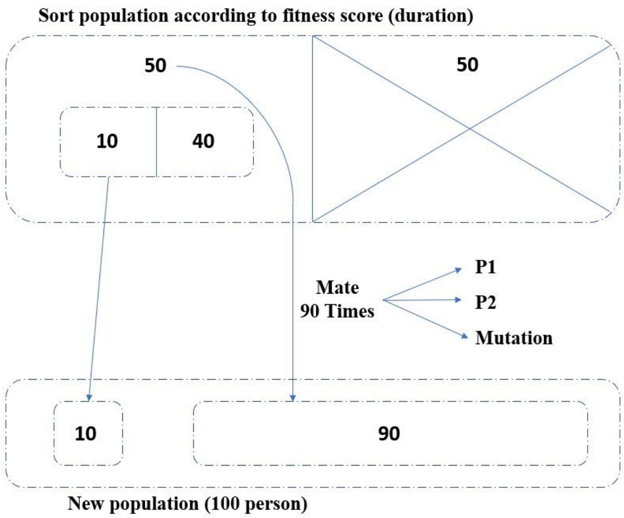

FIGURE 18. Sorting the people according to the duration.

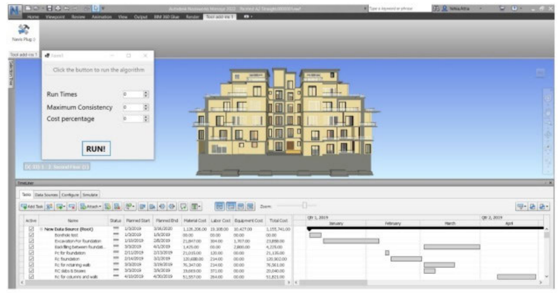

FIGURE 19. Extension of the BIM model.

the right balance between reducing duration and controlling costs. The second aspect that is considered within the "Cost Percentage" is "cost duration." This parameter sets a limit on the increase in the original cost. In this research, the optimization is done using two methods. Firstly, reducing the duration of the project path. After determining the possible duration for an alternative path, the optimization is done without exceeding the specified cost percentage limit. This optimization aims to achieve the minimum possible duration without exceeding the allowed cost increase.

To achieve this, a Genetic Algorithm (GA)-based application using MS Visual C# programming language as an API in Navisworks was introduced and prepared in this research.

V. EXPLAINING THE PROPOSED CODE (GA- ALGORITHM)

The code handles inputs received from Primavera, which come in the form of an Excel sheet with five scenarios: one ordinary normal duration, two compressions, and two delays. The code begins by opening the Excel sheet from Primavera and extracting the data, then transforming it into classes. These classes serve as the models used in the code. Next, it takes the activities and selects an iteration at random. This selection is based on a randomly generated number ranging from 1 to 5, which corresponds to the number of scenarios for each activity. This process is repeated 100 times, resulting in the first population. The first population is then sorted from best to worst based on a fitness function built using the critical path method algorithm (CPM), with the shortest period at the top and the longest at the bottom. The ultimate goal is to shorten the period as much as possible, although it can never be reduced to zero.

Afterward, the top 10 individuals from the sorted population are selected to initialize the second generation. This leaves 90 individuals remaining. The first generation is then split into two halves. The first half, comprising 50 individuals, is used to randomly generate the remaining 90 individuals. Each crossover occurs between two randomly selected individuals, resulting in 90 new individuals. These crossovers can either preserve the first or second option as they are or result in a mutation where a random object from the space we created above is selected.

Next, we check if the desired level has been reached. If so, we stop, and if not, we repeat the process to generate the third, fourth, fifth, and subsequent generations until the same result is achieved X times in a row or based on the number of consistencies entered at the outset (500 was used in this case). Finally, we sort the final population using the CPM fitness function mentioned earlier. The top element in the sorted population is our best option, representing the most optimized iteration possible in terms of time consumption, which, in turn, should increase the cost.

However, as the indirect cost is significantly reduced, the overall cost is reduced as well. Finally, the best result is output to a file, which is then transferred back to an Excel sheet created in the output file's path. Multi scenarios have been tested to create the proposed algorithm with thousands of solutions. The variation of the optimal solutions, the sensitivity and accuracy of calculation of the optimality, the time taken to find the optimal solutions, the cost reflected from the analysis time, and the need for high computational power and resources for increasing the scenarios and solutions are the main causes and basic criteria have been expressed to create the proposed plugin. This will be easy for to user to deal with, It is like the ERT technique (optimistic, most likely, and pessimistic) but with dual numbers (or percentages) in the compressions, the same in extensions, and just one number in the real-time similar to the most likely in PERT. To validate and check the applicability of the proposed plugin, two benchmarks (solved by several methods of algorithms) were tested and solved then a good comparison with the previous results and the results of the proposed plugin.

To satisfy all of these steps, a small project with 136 activities is tested by the proposed GA algorithm with its indirect costs as shown in Table 1. The proposed algorithm, with a mutation rate of 0.5%, arrived at the optimal solution after approximately 200 iterations, as indicated by the 'Run Times' data. Moreover, the algorithm ran for 500 iterations to ensure maximum consistency, as stated under the 'Maximum Consistency' category. The 'Cost Percentage' in this study was 10%.

TABLE 1. Time-cost of total activities.

Alternative spaces of construction	Duration (Days)	Budgeted Total Cost ($)
Normal project	439	1,155,735
First Compression project	333	1,173,395
Second Compression project	280	1,179,294
First Delay project	454	1,164,364
Second Delay project	493	1,163,703

VI. VALIDATION OF THE GA-API MODEL

To evaluate the effectiveness of the proposed GA-API model approach, a benchmark problem introduced by Liu et al. [62] was conducted as a validation problem involving seven predefined activities. Table 2 showcases the available activity options (along with the corresponding difference in the number of days of crashing or delaying, as indicated in the ''Option/Mode'' column), their corresponding durations, and costs for the project consisting of seven activities proposed by [60], which were optimized by [61] and [62]. The new GA-API model was compared to three previous models to determine its performance in a deterministic environment, which are:

1. [60] Utilized the GC method.
2. [61] Employed MAWA with a GA-based strategy.
3. [58] Used RKV-TCO with a GA-based genetic algorithm.

The results of comparing the GA-API model approach with the [58], [60], and [61] approaches are presented in Table 3, which displays the time and cost values for each one and the proposed algorithm (code). The GA-API algorithm outperformed the other works in the fourth generation. Specifically, the GA-API model achieved a project time of 61 days with a $142,500 cost, which is two days less than the optimal solution, and a reduction in cost by $83,000. The cost savings from this model come from its ability to improve both time and cost by using the Cost Percentage value, as previously described in Figures 19-14 respectively.

VII. BENEFITS OF THE INTEGRATION OF GENETIC ALGORITHMS (GA) WITH THE BIM-5D MODEL

More construction in developing countries such as Africa or SMEs using fuzzy mechanisms produces a high number of building infrastructures. In other countries, they used different evolutionary algorithms to enhance the construction sectors.

there are many evolutionary algorithms like evolutionary strategies (ES), evolutionary programming (EP), particle swarm optimization (PSO), and differential evolution (DE) that are used in the industry and construction projects in the planning phase. The complexity and the non-compatibility between these algorithms and planning software are the most common problems for using it at different companies and firms. In addition, these need the expertise to deal with it

TABLE 2. Case study 1 [58].

Activity description	Activity number	Precedent activity	Option/ Mode	Duration (days)	Direct cost ($)
Site preparation	1	-	1	14	23,000
			2	20	18,000
			3	24	12,000
Forms and rebar	2	1	1	15	3,000
			2	18	2,400
			3	20	1,800
			4	23	1,500
			5	25	1,000
Excavation	3	1	1	15	4,500
			2	22	4,000
			3	33	3,200
Precast concrete girder	4	1	1	12	45,000
			2	16	35,000
			3	20	30,000
Pour foundation and piers	5	2, 3	1	22	20,000
			2	24	17,500
			3	28	15,000
			4	30	10,000
Deliver PC girders	6	4	1	14	40,000
			2	18	32,000
			3	24	18,000
Erect girders	7	5, 6	1	9	30,000
			2	15	24,000
			3	18	22,000

TABLE 3. Experimental results.

Approaches	Criteria	
	Time	Cost ($)
M. Gen and R. Cheng, [61]	79	256,400
D. X.M. Zheng, S.T. Ng, and M.M. Kumaraswamy, [60]	66	236,500
Magalhães-Mendes, [58]	63	225,500
The proposed algorithm, (code)	61	142,500

and its mistakes which makes the cost overrun related to the uses of it. Now, at the BIM time which spread and became a mandatory document in construction projects. The improvements and developments of BIM are always done by adding add-ins within its software that make it more compatible, easier, and not need the expertise to use it. That means it covers all the previous problems traditionally. So, to make the proposed integration of genetic algorithms (GA) with the BIM-5D model via Navisworks applicable and the accuracy of time and cost estimation in construction projects a good comparison has been done with other evolutionary algorithms (GA, PSO, MOEA, JA, and A-JA) in the bellow study. This comparison has been done related to a case study mentioned at [63], that dealt with sixty-three activities in a construction project. The durations, relationships, and all the data of the project were taken from [66] also. Table (4) shows the final result from the previous studies and the proposed integration in this study.

The results show the time and cost values for each one and the proposed algorithm (code). The GA-API algorithm outperformed the other works in the fourth generation. Specifically, the GA-API model achieved a project time of

TABLE 4. The comparison between the proposed integration and other different algorithms.

Project	Objective	GA	PSO	MOEA	JA	A-JA	GA-API
63-activity	duration	624	623	621	618	616	557
	cost	5,334,600	5,282,450	5,201,750	4,990,500	4,911,250	4,891,230

557 days with a $4,891,230 cost, which is 59 days less than the optimal solution, and a reduction in the cost of about $20,020 related to an optimal cost with different methods.

VIII. CASE STUDY

Fig. 20 shows a five-story concrete residential building with an area of 742.19 m^2. This building is located in Cairo, Egypt. The project was created in Autodesk Revit 2022 and then imported into Navisworks Manage 2022 to utilize the suggested framework. The client provided a list of items to the contractor, who quoted a price based on the unit price (UP) contractual arrangement. All costs were expressed in US dollars (US$). Cost and pricing estimates were determined, and the project was scheduled using the Primavera P6 schedule database. Additionally, the cost breakdown for each item was determined by combining the cost list and schedule estimates.

To estimate the cost, the proposed framework used the price list to multiply the number of units of each item taken from Navisworks. The unit price (UP) approach was applied, which means that the employer paid the contractor based on the completed items. The generated cash flow worksheet in the proposed framework consists of formulas based on specific inputs and assumptions. The direct costs were estimated monthly from the schedule and automatically inserted into the monthly spreadsheet. The default indirect expense amount was 10% of direct costs.

The direct and indirect expenses were added together to calculate the total cost. The total value was then obtained by adding a percentage markup, which was set at 10% in this model. Typically, owners hold back a percentage of the client's fees until the project is completed, known as retention. In this case study, a 5% client retention rate was assumed at the end of each month. The contractor's default amount was a 10% advance payment to cover mobilization expenses and accelerate the project's start. The Power-BI dashboard was used to calculate the cash flow, and the results are presented in Figures 21-22 respectively.

IX. RESULT AND DISCUSSION

By using GA, the 5D BIM API model can optimize both its cost and duration, resulting in more efficient project completion. This work strategy enables the model to complete all project activities in less time and at a lower cost than the typical approach. Therefore, the outcome is cost and duration optimization for the 5D BIM API model through the use of GA, allowing for more streamlined and cost-effective project completion.

The utilization of this operational approach enables the model to achieve completion of the entire project, including significant activities, in a shorter time frame and with reduced expenses compared to the conventional method. Additionally,

FIGURE 20. BIM Model for the case study.

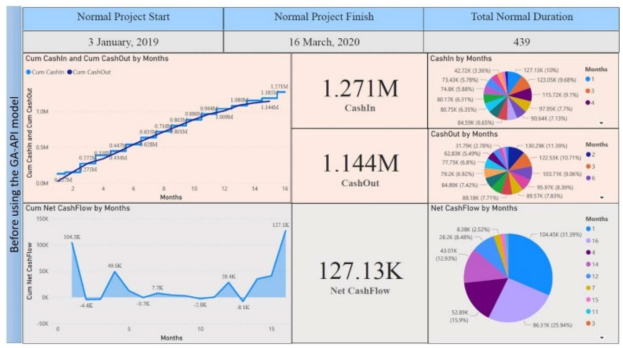

FIGURE 21. Cash flow dashboard for a normal 5D BIM model.

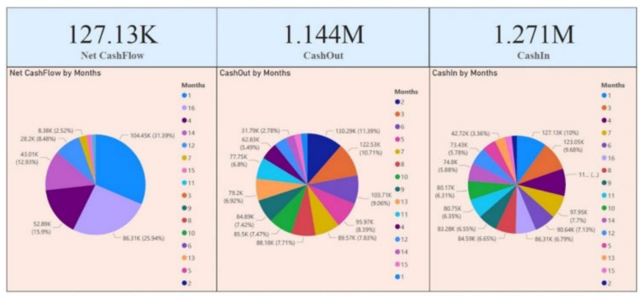

FIGURE 22. Cost per month for normal cash flow.

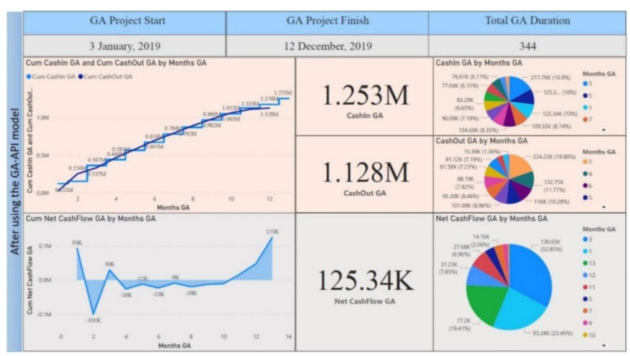

FIGURE 23. Cash flow dashboard after using the GA API model.

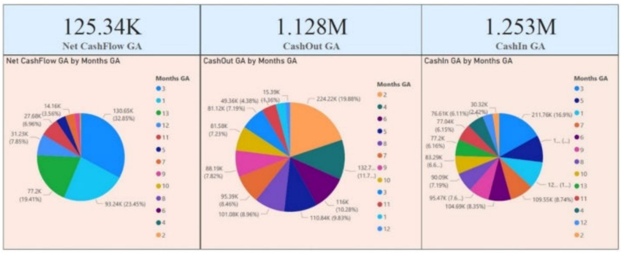

FIGURE 24. GA API model monthly cost.

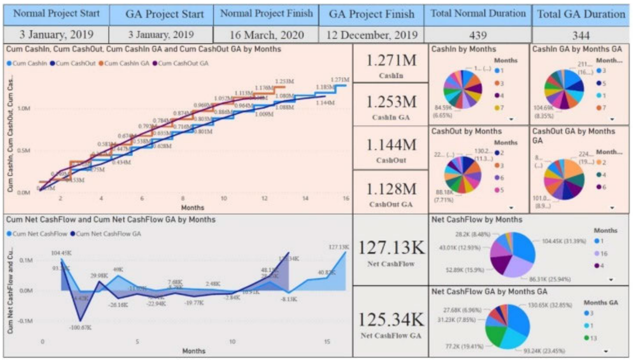

FIGURE 25. Cash flow dashboard illustrates the results before and after the GA API model.

the interface module of the 5D Building Information Modeling program (Navisworks) has been enhanced with a plugin that uses GA with numerous runs to identify the ideal critical path technique for optimal project time and cost. The study initially involved planning the required path method for the project. After estimating the indirect cost, it was determined that the standard project would take (439) days, with a cost of ($1,271,306). However, with the incorporation of the Genetic Algorithms (GA) model as an application programming interface (API) in Navisworks, the project was completed in (344) days at a cost of ($1,253,360), as shown in Figures 23-24.

When the optimized values were utilized, the project time was reduced by 20%, and the project cost was lowered by $17,946, as shown in Fig. 25.

X. CONCLUSION AND FURTHER WORKS

The objective of this study is to improve the efficiency of construction projects regarding their overall duration (with different five scenarios of project time) and expenses. A time and cost optimization technique using genetic algorithms was proposed and applied to the five-dimensional (5D) building information modeling interface. The research showed that the proposed algorithm (code) is a technique that outperformed other optimization methods, resulting in a reduced total project time and cost. Although 5D BIM research has advanced, combining BIM with artificial intelligence methods can yield even better results, especially in terms of project costs and cash flows.

This study illustrates standardized procedures and provides a tried-and-true method for integrating AI methods and genetic algorithms with the 5D BIM interface. The GA BIM model used in this study is a significant contribution as it enhances the optimization model's accuracy and speed. This model can be applied to various multi-objective optimization problems, and its integration with existing software gives a lot of benefits to developers and users. Traditionally, planners and cost estimators spend significant effort and time creating scheduling, planning, and cost estimations. However, the proposed algorithm solves these problems by integrating costs and schedules and avoiding potential problems in future construction. The study's findings supplement earlier research in improving cost estimates and creating 5D BIM-based centralized cost and cash flow management systems.

Additionally, this research contributes to the body of knowledge in 5D BIM and AI methodology and applications. With computing technologies continuously improving and BIM becoming more common in construction projects, optimization through AI and algorithms has great potential. Finally, the following points can be summarized as the main conclusions of the research:

(1) When considering both time and cost, developing a creative solution to solve problems is crucial to maximizing project management effectiveness and achieving project goals.

(2) This study demonstrates how project cost and duration change over time, accounting for the impact of indirect costs on the cost-duration relationship.

(3) To enhance convergence, precision, and rationality, and avoid getting stuck in a partial optimal solution trap, adjusting parameters such as the fitness function, coding mechanism, and chromosomal composition form, and modifying solution flow is essential.

(4) The proposed 5D BIM GA model was tested through several simulations, which involved a limited number of activities. The results confirm the effectiveness of the model in optimizing project duration and cost.

(5) The 5D BIM GA model enables planners/managers to handle more compressions (time cost trade-off) and delays, allowing for more significant time and cost savings.

(6) The 5D BIM GA model can be applied to whole megaprojects, providing more precise results and greater time and cost savings by including more activities.

Further research can be conducted to reinforce the findings and address other challenges in building projects. For instance, the optimization model can be modified in several ways to enhance project management:

(1) Resource allocation and leveling considerations can be included in the model to improve its accuracy. Moreover, exploring additional building alternatives for each activity can help address various challenges and enhance the optimization problem's results.

(2) The optimization model can also be modified to optimize for cost with time to improve project efficiency.

(3) To improve the accuracy of results for megaprojects, the model can be made to receive more than five options,

including two for compressions, two for delays, and one for normal.

(4) Lastly, the performance of both the wall API model and the critical path method can be enhanced through modifications to the optimization model.

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