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A Review of Genetic Algorithm as a Decision-Making Optimization Tool in Project Management

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Project Management requires a lot of decision-making, with chances of making a better decision increasing with an increase in available data. However, decision-making becomes increasingly difficult and complex as available data increases. The problem that this paper address is the lack of the ability of the rational human mind to process a large amount of data within a short period, thereby making poor decisions that could be influenced by lots of biases and reducing the chances of finding an optimal solution. This presents the need for optimization in decision-making with the aid of non-human intelligence/Artificial Intelligence. Therefore, the objective of this paper is to access the impact of Genetic Algorithms as a tool that can facilitate decision-making without sacrificing useful data that could optimize decision making. This study provides a review of genetic algorithms as an optimization tool for decision-making in project management. A comprehensive study is conducted on relevant literature from reputable journal databases. The study highlights the concept and benefits of genetic algorithm, followed by the drivers, as well as the barriers to its adoption. Findings from this paper will provide an insight into the research trend, level of adoption, and potential research areas in the use of genetic algorithms as a decision-making optimization tool. This study is expected to help project managers make a more informed decision in the adoption of decision-making optimization tools as using the right decision tool will free the human mind from mundane tasks to perform more creative tasks.

Key Words: Genetic Algorithm, Project Management, Decision-making, Intelligent Decision

Introduction

Decision-making is the process of considering different options and ideas and arriving at a judgment to take deliberate action on how to allocate resources to achieve the desired goal (Haidar, 2015). Project management is a difficult decision-making process including constant time and cost constraints. The majority of project management issues revolve around planning and scheduling decisions (Gonçalves et al., 2008). The success of a project is determined to a large extent by the quality of decisions made by project managers throughout the project life cycle. The more data available, the better the chances of making an optimal decision by the project manager. However, decision-making becomes increasingly difficult and complex as available data increases hence, presenting a need for an intelligent decision-making support system. Intelligent decision-making generally refers to the application of Artificial Intelligence (AI) in making decisions. One of the major Intelligent optimization tools in decision making is Genetic Algorithm (GA).

A Genetic Algorithm (GA) is a search algorithm based on the mechanics of natural evolution. It loops through available possibilities to select the best combination of variables for optimum or near optimum decisions. It is an efficient optimization system for solving problems with many constraints, uncertainties, and an abundance of feasible solutions. GA is suitable where fast decisions are needed due to its ability to use successive evolution of two acceptable solutions to form the best features. Problem-specific knowledge can also be incorporated to guide the search and decision process of a GA (Haidar, 2015; Katoch et al., 2021).

The objective of this paper is to access the impact of Genetic Algorithms as a tool that can facilitate decision-making without sacrificing useful data that could optimize decision-making. The study provides information on the current level of adoption and application of Genetic algorithm in project management decision-making, the research trend, and the limitations which are potential research areas to improve its adoption. The problem that this paper address is the lack of the ability of the rational human mind to process a large amount of data (big data) within a short period, thereby making poor decisions that could be influenced by lots of biases, reducing the chances of finding an optimal solution.

Background

A study by Janssen et al (2017) identified the main challenge in decision-making with big data as the inability to understand and use the data to create value by dealing with the complexity of the data and making meaning out of it. Big data analysis is a time-consuming task that requires the use of advanced cognitive systems (Gupta et al., 2018). This analysis reveals relationships, trends, and patterns that the human mind may not be able to unravel. In the present data-driven society, big data analysis avail organizations the power to make better decisions and stay competitive (Shamim et al., 2019). This presents the need for a more efficient system capable of processing such big data to assist the human mind in decision-making. Also, making decisions with the human mind is impaired by biases such as irrelevant socio-cultural constraints and cognitive bias when dealing with incomplete datasets (Parry et al., 2016). An AI decision-making system is free from such biases, thereby portraying a true description of the dataset by letting the data speak for itself. This is suitable for the dynamics of construction projects especially in dealing with the planning of cost, time, and human resources. AI is simply the ability of machines to perform human-like activities by learning from experience. GA is the AI decision-making optimization tool considered in this study.

GA has demonstrated its potential as an optimization tool through its application in multiple constraint scheduling, time-cost trade-offs, critical path problem, resource leveling, facility layout, and finance-based scheduling (Ancveire & Poļaka, 2019; Gonçalves et al., 2011; Haidar, 2015; Katoch et al., 2021; Milios et al., 2013; Ramzan et al., 2012; Zhu et al., 2011). The current success in the use of GA as a decision-making optimization tool could be attributed to its drivers such as the ability to process multiple solutions simultaneously, fast output, ability to select solutions based on the fitness value assigned to each chromosome, ability to find the global optimum and avoid becoming stuck in a local optimum, ability to solve poorly understood problems, and the ability to change fitness functions depending on the desired solution (L. Chen et al., 2019; Haidar, 2015).

Despite the above-listed GA benefits, there are still some setbacks that limit the application of GA as a decision-making optimization tool. A major limitation of GA is the cost of developing a robust GA optimization model because of its complexity and the amount of time needed for its development

(Haidar, 2015). Also, solution coding with GA could be problem-specific with architecture that may not be easily applicable to another problem (Ancveire & Poļaka, 2019).

Methodology/Approach

The systematic review method was used in this study. This method is primarily concerned with planning, identifying, and evaluating existing literature to obtain and analyze data from them (Ayodele et al., 2020). Systematic reviews answer specific questions, instead of providing generic literature summaries on the research area (Khan et al., 2003). The Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) method of system review was adopted. PRISMA method was adopted for this review because it can be used to report a wide array of systematic reviews and is suitable for assessing the benefits and disadvantages of a method/technology. Peer-reviewed journal articles were obtained from Scopus and ASCE databases. Relevant articles were also obtained from Google Scholar. Only articles related to Construction Management and Project Management are considered in this study. Due to the rapid evolution in technology, only materials from 2000 are considered to ensure that current information is obtained. The following keywords were used to search for relevant articles on the databases listed above “Genetic algorithm” AND (“Decision making” OR “Decision-making”) AND (“Construction” OR “Project Management”). Fig. 1 shows the research process

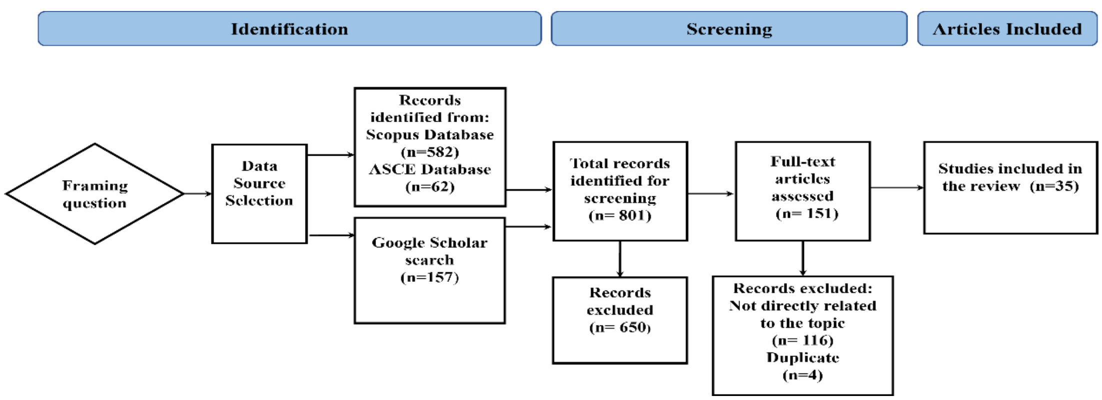

Fig. 1. Systematic review process using the PRISMA method

Analysis and Results

Concept of Genetic Algorithm in Decision-making

Inspired by the biological evolution process, Genetic Algorithm (GA) are search algorithms based on the principles of natural selection and proposed by J.H Holland in 1975 with features like chromosome representation, operators, crossover, selection, and fitness selection (Andre et al., 2001; Sivanandam & Deepa, 2008). The operators are biologically inspired and emulate the Darwin survival theory by selecting chromosomes based on their fitness value (Haidar, 2015; Katoch et al., 2021; Scully & Brown, 2009). GA can efficiently use previous information on new search points to project higher performance when randomized by combining strings containing partial solutions. GA differs from other decision-making optimization tools because they regulate variable representation and exploit similarities among high-performance strings, making them difficult to fool even for challenging functions (Haidar, 2015; Sivanandam & Deepa, 2008). Fig 2 represents the process of the genetic algorithm where A and B are the parent chromosomes and A' and B' are the offspring (next generation) chromosomes. a_{1-4} and b_{1-4} represent the genes contained in the chromosomes.

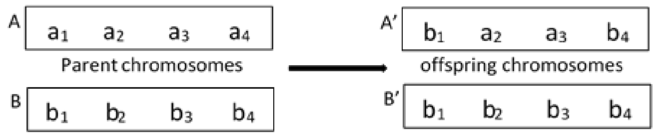

Fig. 2. Genetic Algorithm process

The initial generation of GA is the starting point for optimization with each chromosome assigned a fitness value by the fitness function based on its capacity to solve a given problem (Katoch et al., 2021). The Pareto fitness function called the maximum fitness function is a popular multi-objective fitness function for genetic algorithms and is represented mathematically by equation 1 (Elaoud et al., 2007). On each iteration of the GA, the generation passes through a series of random processes before forming a new generation. Consider two different chromosomes a and b from the same generation

$$F(x_a) = \max_{a \neq b} \left[\min_{1 \leq s \leq k} \{ f_s(x_a) - f_s(x_b) \} \right] \quad (1)$$

Where a and b and two distinct designs in a particular generation and $F(\chi_a)$ represents the fitness of the a^{th} design

The process of GA optimization is controlled by several operators such as selection, mutation, crossover, encoding, and adaptation. Encoding is the process of converting the available information to a format easily recognizable by the GA such as binary and octal. Crossover is the random combination of two or more fittest parent chromosomes to form an offspring chromosome. Mutation ensures that genetic variation is maintained from one population to the next, while the selection operator determines which strings that will participate in the formation of a new generation (Katoch et al., 2021; Sivanandam & Deepa, 2008b). The workflow of GA involves selecting the initial population by the fitness function based on their fitness values. Reproduction is the next step which involves the crossover of parent chromosomes and the mutation of genes of the offspring chromosomes to ensure that the fittest genes are selected. If the output at this stage is satisfactory for the problem, the process ends, if not, the output serves as the new population, and the process is repeated until satisfactory solutions are obtained.

Applications of Genetic Algorithm in Project Management Decision-making

GA has been applied in different fields of engineering (Katoch et al., 2021). This section reviews the common areas of project management where GA has been successfully applied.

Time-Cost Tradeoff

The Time-Cost tradeoff analysis is a crucial part of construction project planning with the aim of selecting the best resources and procedures to complete a project within the required timeframe and at the lowest possible cost (Haidar, 2015). Time-Cost Tradeoff Problems (TCTP) generally arise when the timeframe for a segment of a project has to be reduced to accommodate unanticipated setbacks to meet up with the set deadline (Mokhtari et al., 2011). Wuliang & Chengen (2009) proposed a GA-based solution to Discrete time-cost tradeoff problems (DTCTP). The DTCTP supposes that project activities' durations are distinct, non-increasing functions of a single amount of non-renewable resource. This study proposed a solution to a well-known project scheduling problem—DTCTP to help project managers balance project duration, cost, and available resources. Their approach is based on predefining the resource price, renewable resources related to the project cost including direct and indirect cost, every activity can be performed in a crashing way with the project direct cost used to shorten the duration of each activity. This model developed by the authors balanced three constraints—time constraints, renewable resource constraints, and cost constraints.

Resource Leveling and Resource Constraint Scheduling

Resource leveling in project management is a method used to maintain a smooth flow of construction resources and to avoid daily fluctuation in resource demand (Haidar, 2015). Resource-constrained project scheduling problem (RCPSP) deals with a situation in which the workforce available to perform tasks are limited, with each job having a deadline and a penalty for failing to meet the deadline (Cavalcante et al., 2013; Lova et al., 2009). Gonçalves et al., (2011) proposed a GA approach for RCPSP. The method involves the combination of biased random-key-based GA, a schedule generation scheme, an improvement procedure, and a chromosome adjustment procedure. The main role of GA in their approach is to evolve the chromosomes, which represent the priorities of the activities. The result indicated that the approach performed well against other algorithms and even yielded new best-known solutions for several benchmark test cases.

Material Delivery Schedule

An optimized material delivery schedule has the potential to reduce costs in construction. Fung et al. (2008) applied GA to multi-storey tower block construction by optimizing storage, distribution, and transportation. The test result showed a reduction of 15% in the total transportation cost. Anvari et al., (2016) developed a multi-objective GA-based optimization tool for manufacturing, transportation, and assembly of precast construction projects with the main objective of reducing project completion time. The authors believe that it is necessary to assess the cost and time decision implications from manufacturing up to assembly. This GA algorithm compared to other algorithms can capture real-life situations because of its high degree of flexibility. It is expected to help project managers select the best methods for different levels of prefabrication bearing in mind the total cost and time. This GA algorithm proved to be better than other heuristics when compared in small and medium-size instances but not in large instances.

Finance-Based Scheduling

Availability of cash at the right time during a construction project execution is a common challenge faced by contractors which significantly alters the project schedule. This in turn affects the profitability of a construction project (Fathi & Afshar, 2010). It is necessary to maintain a good and realistic cash flow scheduling throughout a project to avail contractors with funds when needed. A finance-based schedule entails adjusting the project schedule to meet up with constraining cash flow. GA has been applied by researchers because GA is less problem-dependent and enables project managers to arrive at sub-optimal solutions in situations where dynamic programming fails (Yu et al., 2012) itemize finance-based scheduling problems (Alghazi et al., 2013; Ali & Elazouni, 2009; Fathi & Afshar, 2010). Fathi and Afshar (2010) proposed a GA-based multi-objective optimization model for finance-based construction project scheduling that facilitates the decision-making process for the best cash procurement line of credit using the general concept of non-dominated sorting genetic algorithm with elitism. The model selects optimum solutions from a set of optimal nondominated solutions based on the defined order of priority of the objectives. In some situations, however, finance-infeasible offspring chromosomes arise when the traditional crossover and mutation operations are performed (Alghazi et al., 2013). To boost GA's performance by addressing the issue of reproducing finance-infeasible offspring chromosomes, Alghazi et al. (2013) developed a repair algorithm that works by changing the start times of activities to ensure that cash flow never shows higher finance needs compared to the cash limitation. The repair algorithm outperformed the other two treatment methods for finance-infeasible chromosomes—discarding and penalizing the infeasible chromosomes.

Multiple Constraint Scheduling

Project scheduling is a complex process with a lot of considerations for successful project delivery with different short and specific approaches for each scheduling constraint, thereby requiring the combination of multiple heuristic rules for decision making. GA, however, offers a single heuristic solution to such problems. Chen & Shahandashti (2009) proposed a hybrid GA and simulated annealing (SA) method for generic multiple projects scheduling with multiple resource constraints. Due to the random searchability of the GA-SA hybrid, the model can be applied to various kinds of optimization problems. Dawood & Sriprasert (2006) also applied GA in Multiple Constraint Scheduling. The authors considered four major construction constraints: Contract constraint (time, cost, quality, special agreement); Physical constraint (technological dependency, space); Resource constraint (availability, capacity, perfection); and Information constraint (availability and perfection). To resolve these constraints, they employed the techniques of Resource allocation (to reschedule projects to efficiently utilize the limited resources) and Resource leveling (adjusting task dates, duration, and resource allocation, to fix the overallocation of resources while maintaining the original project duration).

Drivers of Genetic Algorithm in Project Management Decision-making

The GA operators—selection, mutation, and crossover, which are based on the laws of evolution give GA its competitive edge over other optimization methods (Fourie & Perold, 2003; Katoch et al., 2021). Its adoption for decision-making optimization in project management is driven by its unique advantages that include genetic mutation, excellent parallel compatibility, suitability for large-scale optimization problems, efficiency in handling noisy functions, and generates multiple global optimal solutions (Ancveire & Poļaka, 2019; Haidar, 2015; Ko & Wang, 2010; Sivanandam & Deepa, 2008). Traditional optimization methods like the physical, schematic (graphs and charts), and linear programming methods usually become infeasible when there are multiple constraints and uncertainties in achieving an optimal/near-optimal solution, hence, a need for an intelligent method for decision-making optimization such as GA (Haidar, 2015; Sivanandam & Deepa, 2008a).

Table 1
Comparison of Genetic Algorithm with Traditional Optimization Methods

Genetic Algorithm	Traditional Optimization Algorithms
• Designed for both continuous and discrete optimization problems.	• Designed for either continuous or discrete problems
• More robust because they search for solutions from a sample population.	• Less robust as they mostly search from a single point
• Not easily confused as they work with encoded parameters and not the actual parameters	• Can be fooled by problems with complex parameters
• Uses objective function.	• Uses derivatives
• Are based on probabilistic modeling.	• Based on deterministic modeling

Linear programming uses mathematical/analytical techniques to solve optimization problems with different linear constraints (Haidar, 2015). The ability of GA to be initiated with a population of solutions makes it possible for a global optimum to be obtained with a GA. GA differs from other optimization methods in the sense that the properties of its fitness function are not bound by any mathematical constraints and is designed to maximize tradeoff by exploring new search locations and utilizing already obtained information (Sivanandam & Deepa, 2008). Table 1 summarizes the unique benefits of GA compared to other optimization techniques.

Challenges of Genetic Algorithm in Project Management Decision-making

Despite the numerous unique benefits provided by this innovative decision-making optimization tool, there are still some barriers affecting its adoption in project management decision-making in the construction industry. Some of the challenges include the amount of time needed to develop GA for a particular project, the complexity, the possibility of premature convergence, and its inability to guarantee a single best solution.

Rate of convergence and speed are considered important factors in determining the performance of an algorithm. A GA converges when there is no change in the chromosomes from one iteration to the next. Premature convergence occurs when the optimization problems coincide too early, leading to the algorithm being trapped in a local optimum and generating poor results (Andre et al., 2001). A smaller generation may result in the GA converging too early, hindering the chances of the GA to reach optimal/suboptimal solutions (Haidar, 2015). Andre et al. (2001) proposed a solution to premature convergence in GA by introducing scale factor and adaptive study interval. The method showed an improvement in convergence but negatively affected the speed of the algorithm.

Selecting an appropriate initial population is necessary for the use of GA in decision-making as the output depends on the initial sample population. Typical examples of such situations in construction project management include the inability to identify the level of knowledge of a team member required to complete a particular task, keeping up with the skill development of team members, and the inability to prioritize activities involved in a project (Ancveire & Poļaka, 2019; Li & Dong, 2018). A very large population could increase the processing time of a GA while a very small population could lead to a poor output (Katoch et al., 2021).

Conclusion

Project management is mostly about decision-making and with the advent of big data, which is aimed at making more informed decisions, it has become increasingly difficult for the human mind to process such data without the aid of non-human intelligence. The study showed that GA has proven to be efficient through its practical application in project management situations like time-cost tradeoff, finance-based scheduling, multiple constraint scheduling, resource leveling, and material delivery. The success of GA in these contexts could be attributed to its operators—selection, mutation, and crossover, that mimic the biological evolution process. GA differs from other traditional optimization algorithms mainly because it can be applied to both discrete and continuous optimization problems and can also search for solutions from a sample population and not a single point, thereby greatly reducing the possibility of getting trapped in a local optimum. GA however has its downside like the complexity required for its development and the possibility of premature convergence when an inappropriate initial sample population is selected. GA has demonstrated to be efficient despite its few limitations. Further research on the challenges of GA could address the current setbacks faced by GA in decision-making.
The contribution of this paper is a comprehensive review of GA with a focus on the area of Project Management decision-making. A simplified concept of GA and its applications in project management are discussed.

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