A MULTI-OBJECTIVE OPTIMIZATION APPROACH FOR THE cost-time-quality trade-off in construction projects

Dr. Kamal Jaafar - Professor
Co-author: Prof. Mohamad Watfa - Associate Dean
UNIVERSITY OF WOLLONGONG IN DUBAI, UNITED ARAB EMIRATES

Abstract: The project management triangle is described as the factors of time, cost, and quality of a project. These triple constraints are considered part of the major tangible criteria for determining the success of a project (Joslin and Müller 2016; Kabirifar and Mojtahedi 2019). In order to maintain a successful standing for a project, constant monitoring and modification are done to these three factors throughout a project's lifetime. However, modifying one factor has effects on other factors, which is a trade-off that many construction projects struggle with (Van Wyngaard et al., 2011). This trade-off can have a considerable measure of negative impacts on the project by diminishing the quality, and increasing the actual duration or incurred costs. Hence, project managers and planners must put a considerable amount of effort into ensuring suitable valuation of the variables which affect those factors. Although many studies have been conducted on the optimization of time, cost, and quality, most of them fail to address some of the main components of the triple constraints, such as labor allocation, productivity, and quality. Additionally, managing the quality of a project is done during the construction phase rather than the planning phase, which can have tremendous effects on the final quality of the project (Aljassmi and Abduljalil, 2018). The primary aim of this paper is to present a functional model of time, cost, and quality trade-off optimization while taking into consideration the effects and values of variables such as labor count, productivity, and quality through the use of Multi-Objective Optimization (MOO) and Non-dominated Sorting Genetic Algorithms (NSGA II). This function model will provide a set of optimal solutions and hence provide decision-makers with tools to analyse the state of the project and take actions suiting the project requirements. To demonstrate the effectivity and capabilities of the model, an example from previous literature is analysed to present and visualize several optimal solutions to the variables and trade-off of the time, cost, and quality functions.

Keywords: Project Control; triple constraints; Multi-Objective Optimization; Non-dominated Sorting Genetic Algorithms.

I. INTRODUCTION

A project is the set of sequential tasks and activities required to provide a product or a service. Several factors have an effect on a construction projects state. The project management triangle or triple constraints, which are the time, cost, and quality of a project, are considered some of the major tangible criteria for determining the success of a project. As the understanding of construction management increased, other intangible criteria such as stakeholder satisfaction, safety, and environmental considerations are becoming more recognized due to their value and importance (Silva and Warnakulasooriya 2016). However, these factors are not always direct and their effect can be hard to quantify. Due to the importance of such factors, several studies have been conducted on ways to find optimal values for the variables affecting the success criteria in a project. Thus, the triple constraints remain as the most suitable tangible criteria for determining a project's success (Joslin and Müller 2016; Kabirifar and Mojtahedi 2019).

Many construction projects tend to focus on optimizing areas with the highest deficiencies that show a huge impact on the project (Insja and Sihombing 2017). However, the optimization of one aspect of a project can have an impact on other factors; as optimizing time may affect the cost of the project and so forth. This trade-off occurs when a project variable or several ones are changed causing variation in other variables. As per Van Wyngaard et al. (2011), a change in one variable has an effect on one or both other variables, which a trade-off that usually happens between the triple constraints. They describe that an increase in scope increases time and cost, while a decrease in time decreases scope and increases cost, and finally, a decrease in cost increases time and decreases scope. Hence a variation of one variable will have both direct and indirect effects on the others deeming it necessary to optimize their interdependency based on the priorities set by the conditions of the project (Van Wyngaard et al. 2011). The effects caused by the trade-off could lead the project to be unsuccessful and incur huge losses. Thus, a system that optimizes the values and trade-off among several project functions is needed.

Since it is an issue faced by many construction projects, different methods aiming to control the trade-off were generated such as Fu and Zhang (2016) optimization models. Many studies have been done based on similar models where a single objective function would be generated allowing the suggestion of an optimal solution for that function, and then adjusting the budget and schedule accordingly (Kim 2013). To tackle the issue of optimizing t hree non-linear functions simultaneously, one must look at Multi-Objective Optimization (MOO) models. These models use several techniques in order to present the best fit set of solutions for different functions while taking into account non-domination of the results, diversity, and correlation among the functions.

Through the use of several techniques such as Non-dominated Sorting Genetic Algorithms (NSGA II), Teaching Learning-based optimization, fuzzy optimization and other, researchers have been able to present solutions to the optimization of various aspects in the construction industry (Toğan and Eirgash 2018; Tran et al. 2016). However, to solve the issue of optimization in construction, one must first define the functions to be optimized. Due to the variety of factors and variables considered with the construction industry as mentioned earlier, and the aims of this study; the time, cost, and quality functions will be the main focus of the optimization model. As mentioned, several studies aimed to optimize the project management triangle with different areas of focus. Some studies presented risk as one of the major variables considered in the optimization model, others discussed labor utilization, however, not many studies can be found using the number of labor or their productivity factors represented in the functions themselves (Aljassmi and Abduljalil 2018; Kannimuthu et al. 2019; Wu et al. 2018). Although extensive research on the subject has been done, the findings are not being implemented in real world situations due to the models complexity (Brown 2016). Hence, the aim of this study is to present a simple Multi-Objective Optimization model, solved using Genetic Algorithms, which considers the effect of the number of labor, their productivity, the trade-off, and other variables in the optimization of a construction project's time, cost, and quality to provide decision-makers the tools and data required to enhance the state of a project at all stages.

II. LITERATURE REVIEW

As the complexity of a problem increases, it becomes harder to generate and identify an optimal solution. Hence, many computational tools to define such parameters were created, one of which is optimization. Optimization is a mathematical technique that generates the best fit solution for a given problem within the set of bounds and limits which constrain the main objective function. Through the optimization of the objective function, which is a representation of the concerned variables of the problem, the best fit solution is obtained through the means of minimization or maximization. This process yields an optimal value for the objective function within the problem's bounds and constraints (Kannimuthu et al. 2019).

Looking at single optimization functions provides a wider understanding of the composition of the considered objective functions. Ngowtanasuwan (2013) created a mathematical model that uses integer linear programming to allow cost optimization when the project is to be divided over several contractors. The issue at hand was that each contractor had different abilities, such as the number of construction team's available, time these teams required to achieve tasks, and construction methods to be used which led to incurring different costs at the end of the project. The author's findings concluded that each contractor would have to construct a specific number of houses based on the type and method that fits their abilities which ultimately decreased the total costs and time required to finish the whole project. Although the findings concluded that the total cost decreased, this optimization model can only be used in the decision-making phase when contractors and subcontractors have not been assigned yet in addition to requiring a lot more input to identify all the cost affecting factors in the model, which would have a considerable effect on the provided results.

However, real-life problems such as the ones present in the construction industry are more complex and present several more aspects that require optimization. Such problems which require the optimization of two or more aspects simultaneously are called a Multi-Objective Optimization (MOO) problem (Wang 2016). Through the use of MOO, it is possible to optimize several objective functions where a trade-off occurs. The single objective optimization technique aims to provide the best fit solution; however, it can't be done for MOO since there is no single solution for such problems. Instead, the MOO provides a set of viable solutions, called a Pareto Optimal Solution or Pareto Front, which represents a global minimum or maximum that satisfy the bounds and limits of the objective functions. Each set presented in the Pareto Front is a non-dominated optimal solution, meaning that the solution provides a feasible compromise, or trade-off, between all functions without degrading any of the functions. Finally, after obtaining this data on the solutions and the trade-off between them, the responsible personnel are able to choose one, or several sets, of the solutions presented based on their preferences and requirements (Cui et al. 2017; Panwar et al. 2019).

A. Multi Objective Optimization

Throughout the years many studies have been conducted on ways to solve MOO problems. Some of which include biology, geography, and physics-inspired algorithms. Each category has its benefits and limitations. The main focus of this paper is Evolutionary Algorithms (EA), specifically Genetic Algorithms (GA), which are a subcategory of biology inspired algorithms, due to their simple implementation, applicability to different fields, ability to operate using population solutions, ease of discovering a global optimum, use of probabilistic transition, and ability to solve multi-objective functions simultaneously (Cui et al. 2017; Kramer 2017). Moreover, many studies have been done on the best techniques to solve MOO problems, several of which ranked Non-Dominated Sorting Genetic Algorithms (NSGA II) and basic GA to be the top two for such complex problems based on multiple criteria including the ease of use (Cui et al. 2017; Panwar et al. 2019). NSGA II is a modified version of GA which uses an elitist selection process based on the superiority of the solution through the use of a fitness function and crowding distance (Deb et al. 2002).

In general, the steps of the traditional GA optimization are as follows:

1. Initialize population
2. Select parents
3. Crossover
4. Mutate
5. Survivor selection
6. Repetition

The first step in the optimization process is to generate a population with a random set of individuals, where each solution is referred to as an individual and each gene represents a variable of that solution. The next step is to choose the parent individuals from the population through the use of a fitness function, which is a function that ranks the solutions based on how well they perform with regard to the optimization of the objective functions. After the highest-ranking parent solutions are chosen, the solutions go through crossover to generate a child individual representing genes of both parents. The next step is for the child solution to go through mutation where some of its genes are changed within the set constraints of the variable. Finally, a new population will be selected by choosing the best-fit solutions from the parent population. (Shi et al. 2017; Cui et al. 2017; Panwar et al. 2019).

In NSGA II, a random parent population is generated and goes through tournament selection, crossover, and mutation after being arranged based on each individual's fitness. Tournament selection is a fitness-based process between individuals of the population to choose which will move on to the crossover stage. When the child population of the same size is created, both the parent and child population are combined and sorted according to non-domination and crowding distance; the distance between a solution and other nearby solutions. The new population is then created with the initial size with the highest-ranked solutions. The iteration repeats until the process converges based on the termination criteria set by the modeler (Deb et al. 2002).

Using NSGA II ensures that the optimization model has the following criteria:

1. Applicability to real-life experiences by allowing complex and large-scale variants.
2. Robustness to allow the stability of the objective functions.
3. Diversity of solutions.
4. Non-domination of the solutions.
5. Multiple objective optimization.
6. Ease of modification and implementation.

B. Time-Cost-Quality

Due to their wide range applicability, numerous studies have focused GA for solving MOO in different fields. Several studies have been proposed to optimize factors the factors of time, cost, and quality with the inclusion of different aspects such as the environmental effects, energy consumption, and resource utilization (Jaafar et al. (2021). Notably, the studies conducted by El-Rayes and Kandil (2005); Lotfi et al. (2017); Isikyildiz and Akcay (2020) where each study presented an optimization model to optimize time, cost, and quality in construction projects in an attempt to present the efficiency and benefits of said models. El-Rayes and Kandil (2005) provided a model of time, cost, and quality where their aim was to prove that the quality is an important factor in decision making. Using GA and the quality function they formulated, El-Rayes and Kandil (2005) were able to solve the optimization problem and provide a pareto front that includes quantifying the impact of the quality performance indices and the effect of the quality of each activity. However, one of their main limitations reside in the other objective functions such as valuating time only as the duration taken to complete the task rather than the factors affecting the duration.

Moreover, Lotfi et al. (2017) also presented a model of optimizing time, cost, and quality with the addition of energy and environment in an attempt to define the effects of such "indeterministic" variables on bridge construction. The authors used the e constraint method and augmented e constraint method as the optimization techniques to solve the objective functions. The objective functions were based on the normal, nominal, and compacted values of the variables. Other than the limitations of the e constraint method in which one function is optimized while others are considered as constraints, the results provided are the permissible ranges for the objective functions and do not identify the factors causing an increase in cost or duration.

Similarly, Banihashemi et al. (2020) presented a model that aimed at reducing the negative effects on the environment by providing a single objective function representing the environment with the time, cost, and quality being considered as constraint. After testing their model on 7 different modes, they agreed that the size of the project, number of variables considered, method of estimating unquantifiable variables, and the method of optimization are all critical to the outcome. One of the limitations of their study as mentioned by the authors is "Lack of research resources", which is similar to the previously discussed studies, in addition to the need to use different optimization methods to validate and present better results.

Although the findings of the mentioned studies provided an adequate pareto front, the models do not have enough variables to account for major issues but represent general factors such as duration of completion and total cost in terms of variables. Aljassmi and Abduljalil (2018) MOO model where the authors aimed to optimize time, cost, and quality with a focus on the planning phase rather than the implementation phase where quality is managed as per the authors. Using an optimization technique called Central Composite Design to optimize time, cost, and quality in ceramic tiling activities, the authors were able to provide an analysis of their objective functions while including significant data such as crew size and their productivity as variables of time and cost to help in providing an estimate of the required number of labor in the planning phase. The limitations of their study included the choice of optimization method and the modeling two functions while posing the third as a constraint measure.

Moreover, Monghasemi et al. (2015) present an interesting approach to the triple constraints optimization methods where they used NSGA II and evidential reasoning to analyze the uncertainties of the problems. Their cost function included the cost of delays and other important factors and their quality function used Shannon's Entropy as a measure for quality was used to provide a non-biased weight. Their findings proved to raise efficiency in project scheduling and that the use of NSGA II provides adequate results working with multiple objectives.

Building on the studies mentioned, the findings of the studies concluded that the objective functions, variable composition, type of optimization method, project size, available data, and methods to quantify intangible aspects are all major determinants of the final outcome of the model. While some studies of the aforementioned studies, focus on the triple constraints, as per Aljassmi and Abduljalil (2018), these studies are limited in number, functionality, and many focus on managing quality rather than planning for quality assurance. The optimization models have not been widely used in practice as per Brown (2016) due to their high complexity and limit of variables, among other issues. Thus, this study aims to draw on the literature and create a time, cost, and quality optimization model with a focus on defining the labor requirements and their effect on the triple constraints using NSGA II. The model also aims to be simplistic and provide usability during all stages of a project's lifetime, including the planning, implementation, and maintenance stages to provide decision-makers with a monitoring and control tool.

III. METHODOLOGY

The optimization model will follow the process of NSGA II to optimize the objective functions of time, cost, and quality to provide decision-makers with the necessary tools to better understand the variables affecting those functions and the trade-off among them.

Regarding the function of time (2), many studies such as El-Rayes and Kandil (2005), Heravi and Faeghi (2014), and Banihashemi et al. (2020) look at time in terms of duration to finish a task based on the critical path. However, little data has shown the factors affecting the time function (2) as variables. Aljassmi and Abduljalil (2018), in their optimization problem, look at labor requirements and productivity rates to determine the time to complete a task. Additionally, many studies have provided examples on the qualities affecting the time it takes to finish a task where one of the most important factors was found to be labor experience (Mojahed and Aghazadeh 2008; El-Gohary and Aziz 2014; Durdyev et al. 2018; Abdelkhalek et al. 2020). Based on the approach by Aljassmi and Abduljalil (2018) and the approach from Banihashemi et al. (2020) using the time to finish a task focusing on the critical path, the function of time becomes the follows.

$$Minimize\ Project\ Duration = \sum_{i=1}^{n} \boldsymbol{T_i} \quad (1)$$

$$\boldsymbol{T_i = D_i + M_i} \quad (2)$$

$$\boldsymbol{D_i = \frac{U_i}{L_i + \frac{IP_i}{WH}}} \quad (3)$$

Where:

D_i: Duration took to complete activity (i).

M_i: Miscellaneous time added to activity (i).

U_i: Quantity of work to be done for activity (i).

L_i: Number of labors assigned to activity (i).

IP_i: Imposed productivity for activity (i).

WH: Working hours.

The aim of the first objective function (1) is to minimize the duration of the project while considering the labor requirements as a variable in order to identify the required number of laborers for each activity depending on the quantity of work to be done, labor experience, and working hours. The imposed productivity is a measure of productivity to be assigned based on experience (Aljassmi and Abduljalil 2018).

The second function to be optimized is the cost function (5). As Tran et al. (2016) put it, the cost of an activity is the sum of the direct and indirect costs incurred on said activity. As it is a major focus of this study, the cost of labor and materials are included in the direct costs to identify and optimize their effect on the cost of an activity. The indirect costs are set to be valued as a fixed cost depending on the time taken to finish an activity.

$$Minimize\ Total\ Cost = \sum_{i=1}^{n} \boldsymbol{C_i} \quad (4)$$

$$\boldsymbol{C_i = DC_i + IC_i} \quad (5)$$

$$\boldsymbol{DC_i = (CL_i \times L_i) + (CM_i \times U_i)} \quad (6)$$

$$\boldsymbol{IC_i = CI \times T_i} \quad (7)$$

Where:

DC_i: Direct costs of activity (i).

IC_i: Indirect costs of activity (i).

CL_i: Cost of labor for activity (i).

CM_i: Cost of material for activity (i).

CI: Indirect cost per day.

As quality is considered one of the intangible variables, many studies have been done on ways to quantify and understand the level of quality. Based on several studies, the method proposed by El-Rayes and Kandil (2005) was found to be effective in quantifying quality, in which the weight and performance of certain quality indicators are weighed against the weight of an activity compared to other activities. This approach of quantifying quality has been used by several studies due to its efficiency and effectiveness (Heravi and Faeghi 2014; Tran et al. 2016; Fu and Liu 2019).

$$Maximize\ Project\ Quality = \sum_{i=1}^{n} \boldsymbol{Q_i} \quad (8)$$

$$\boldsymbol{Q_i} = \sum_{i=1}^{n} \boldsymbol{w_i} \sum_{k=1}^{N} \boldsymbol{Qt_{ik} \times wt_{ik}} \quad (9)$$

Where:

w_i: Weight of activity (i) compared to other activities.

Qt_i: Performance quality indicator (k) for activity (i).

wt_i: Weight of quality indicator (k) for activity (i).

The quality function (9) uses the quality indicators, which are set based on the type of activity, in addition to including the imposed productivity and material quality as indicators.

A. Initialization

As mentioned earlier, the NSGA II optimization process goes through several stages to ensure the generation of an optimal solutions front called a Pareto front. The initialization step is the first step in which the first population is generated. The first population is generated randomly which allows the model to create several solutions within the entire range of solutions. The number of solutions in each generation is important as it is the first determinant of the optimality and diversity. The number of individuals will be set as 200 as this many solutions ensures convergence to optimal solutions (Monghasemi et al. 2015). After the generation of the first population with size N, the solutions go through tournament selection, mutation and crossover to create a child population. After the first generation, the parent and child populations are combined to form a new population with size 2N the solutions of this new population are ranked based on non-domination by checking the solutions which are not dominated by any other solutions. The set of solutions (i) which are not dominated by any others are listed in the first front, while the other solutions which the set (i) dominates are listed in the lower fronts. Then the crowding distance, the average distance between an individual and the closest other individuals, is also used to determine a rank. Both the rank of non-domination and the crowding distance are used to create the second population which is composed of the highest-ranked fronts and crowding distance with the original population size N. The model then keeps on repeating these iterations until the termination conditions are met (Deb et al. 2002). **Figure 1** shows the NSGA II loop representation model presented by (Deb et al. 2002).

B. Mutation and Crossover

In NSGA II, the solutions of a population go through crossover and mutation for creating the child population. Crossover is a term that describes the exchange of genes, or variables of a solution, between two solutions to generate new solutions. The generated solutions go through mutation, a random change in variables, to make sure the new solutions are unique and diverse. In GA, the chosen solutions based on their fitness go through crossover and mutation to generate the new solutions. The parent solutions are chosen based on the rank of the fitness function.

C. Software

It is important to represent the results in readable and visual content. Matlab provides the tools to perform both NSGA II and GA with a simple user interface and allows the modification of multiple criteria such as the objective functions, number of populations, termination criteria and many more (Kulik and Protopopova 2020). Based on the study by Abdel-Razek et al. (2010), Matlab was found to be an adequate tool to provide adequate results of NSGA II and GA optimization. (Abdel-Razek et al. 2010).

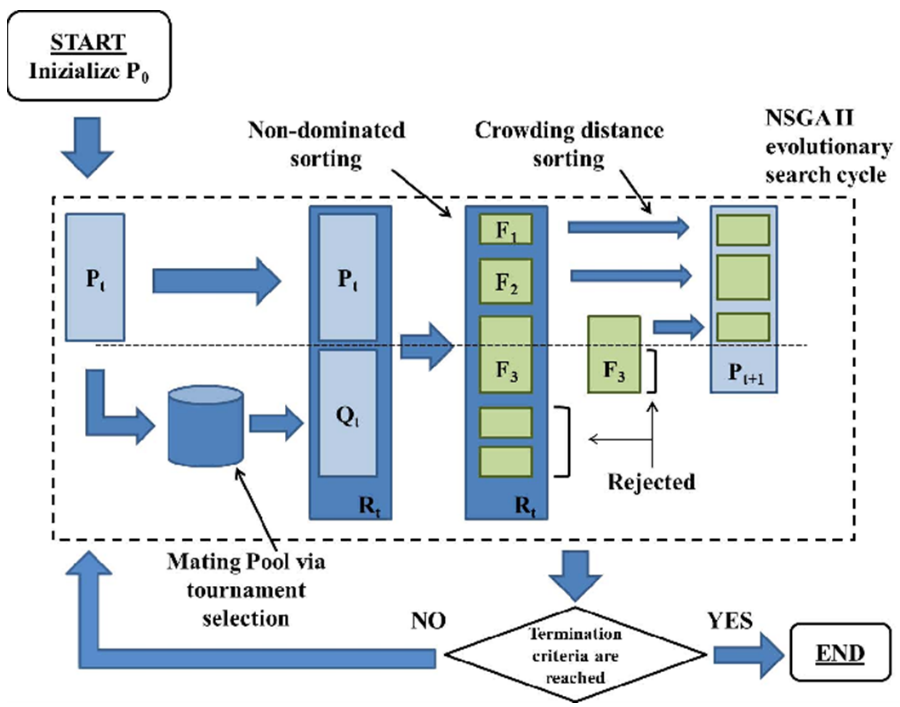

Figure 1: NSGA II representation

IV. APPLICATION EXAMPLE

In order to validate and illustrate the use and benefits of the model presented, an example proposed by previous research is analysed and the model is validated by using both NSGA II and GA to be able to compare the results. The GA method differs from NSGA II by adding a fitness function to rank the solutions of each generation. The method proposed by Koo et al. (2015) will be used for evaluating the fitness function (11). The method they proposed uses the weighted Euclidean distance method in order to create a fitness function through the standardization of the maximum and minimum values of the objective functions, thus creating a fitness function that can choose the optimal non-dominated solutions of each generation (Zhang et al. 2014; Koo et al. 2015).

$$S = \frac{S - Smin}{Smax - Smin} \quad (10)$$

$$F = \sqrt{Wt(ST)^2 + Wc(SC)^2 + Wq(1 - SQ)^2} \quad (11)$$

Where:

ST: Normalized time.

SC: Normalized cost.

SQ: Normalized quality.

Wt: Weight of time function.

Wc: Weight of cost function.

Wq: Weight of quality function.

The project is a road construction project between the towns of Castel Maggiore and Funo in Italy with a focus on the construction of the main axis. The project is made up of 10 activities in which each activity is presented with time, cost, and quality measures based on 3 options alongside the weight of each activity presented by Sorrentino (2013). For the sake of this study, instead of implementing the three options, the limits of the model are assumed to be the highest and lowest values presented by the options as presented in **Table 1**.

Moreover, the data is expanded to account for the quantity of work to be done and the quality indicators. The quantity of work is set to the values in **Table 2** based on the cost and duration of each activity.

Activity	Quantity (m2)	Activity	Quantity (m2)
1	3,500	**6**	2,000
2	1,000	**7**	1,500
3	1,000	**8**	4,500
4	5,500	**9**	1,000
5	11,000	**10**	3,500

Table 2: Project quantities

The two quality indicators are set to be optimization variables in order to remove any bias, and the quality of material and labor are defined as indicators to determine the shared effect of those factors on the quality. The total maximum limits of the project duration and cost are 429 days and $9,000,000, respectively. The model parameters were the following:

- Number of generations: 300
- Population size: 200
- Crossover fraction: 0.9
- Constraint tolerance: 0.01

Table 1: Project dimensions

	Activity	Duration (days)	Cost (dollars)	Weight of activity (%)
1	**Construction excavation**	23-38	132,740-140,345	0.5
2	**Embankment**	1-3	18,344-18,618	12
3	**Geotextile**	4-6	9,235-10,420	9.5
4	**Embankment: recycling soil**	38-59	372,093-377,397	14
5	**Embankment: cement/lime soil**	122-193	1,247,091-1,264,870	14
6	**Road foundation: cement stabilized soil**	14-20	386,245-387,378	10
7	**Road foundation: crushed concrete**	9-13	286,375-287,494	10
8	**Tout Venant**	31-45	5,066,702-5,077,093	10
9	**Protection layer**	5-7	153,725-155,169	9
10	**Wearing course**	21-32	1,065,325-1,071,272	11

These parameters are recommended by several studies such as Tran et al. (2016) and Monghasemi et al. (2015) and are viewed as adequate to generate enough solutions which converge at the optimal solutions. The optimization model was used to search a constrained space to find possible solutions for the presented time, cost, and quality objective functions. The model was successfully able to reduce the search space by choosing non-dominated solutions and focusing on the highly ranked solutions. Presented in **Table 3** is some of the data obtained from the optimization model.

The optimization model was able to generate 71 non-dominated optimal solutions and decrease the search space by converging on the range of optimal solutions. These optimal solutions signify the best possible outcomes within the generations of the model. The correlation and trade-off among the objective functions can be seen in the solutions as the patter in difference between them. The entire set of optimal solutions are presented graphically as a 3D scatter plot, which can aid in visualizing the trade-off among the time, cost, and quality, thus presenting decision-makers with a tool to identify the impact of different scenarios. In order to validate the results, the model was also optimized using GA in which similar results were generated. The comparison between NSGA II, GA, and the results reported confirms that the model is capable of generating sets of optimal solutions for the time, cost, and quality objective functions and present a tool for decision-makers that helps in making decisions regarding the presented variables in order to perform a task and complete the project within the optimal timeframe and budget while having high quality.

Time (days)	Cost (dollars)	Quality (%)
360	8,802,054	71
384	8,222,362	74
376	8,317,960	72
379	8,237,439	76
363	8,452,530	72
390	8,210,974	74
387	8,216,801	74
362	8,437,862	73

Table 3: NSGA II results.

Time (days)	Cost (dollars)	Quality (%)
346	8,386,251	86
331	8,144,886	76
360	8,621,152	83
339	8,322,245	97
335	8,101,903	86
329	8,056,594	95
382	9,102,254	83

Table 4: GA results.

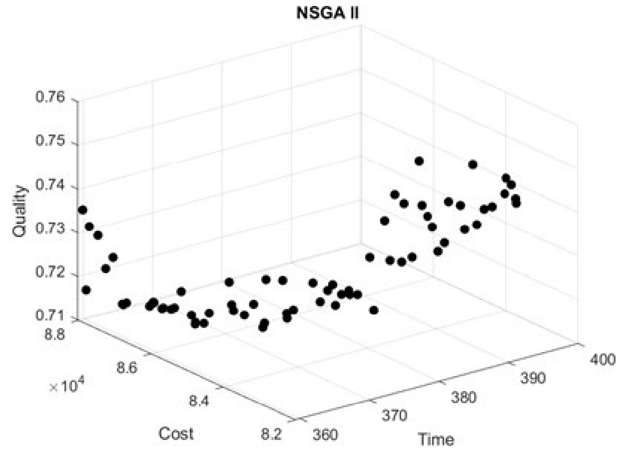

Figure 2: NSGA II Time – Cost – Quality

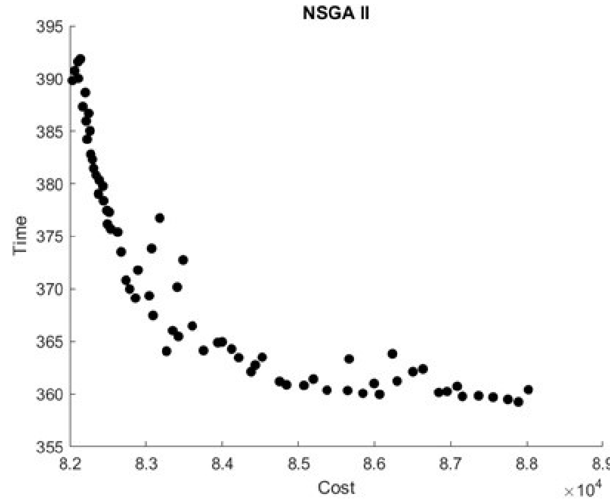

Figure 3: NSGA II Time vs. Cost.

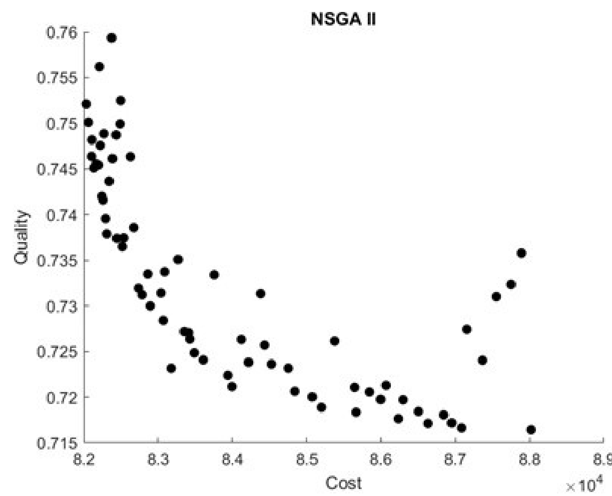

Figure 4: NSGA II Quality vs. Cost.

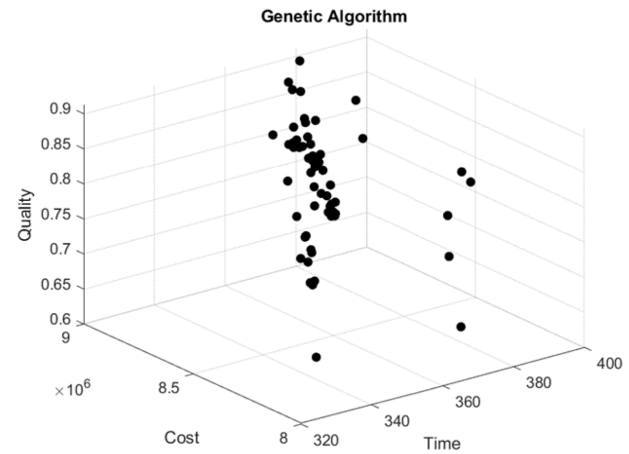

Figure 5: GA Time - Cost - Quality

The data in **Figure 2** and **Figure 5** show the solutions presented by NSGA II and GA. Both optimization methods provided solutions within the limits of the model and adequate trade-off. Figure 3 and Figure 4 shows the time versus cost and quality versus cost, respectively where the convergence of the NSGA II to a range of optimal solutions is visualized. The extreme points also prove that the solutions are diverse. Convergence and diversity are the two main goals of MOO as per Deb et al. (2002) which were achieved in this model. The GA uses a fitness function based on weights which is the cause of the different spread of data shown in **Figure 5**.

V. CONCLUSION

The primary goal of the paper was to present an optimization model of the functions of time, cost, and quality in terms of the variables which have an effect on those functions and introduce the resources, number of labor in specific, as decision variables in the model. Non-dominated Sorting Genetic Algorithm (NSGA II), a biological-based evolutionary algorithm, was used to solve the optimization problem and provide a unique optimal solution in terms of a Pareto Optimal front representing several solutions for the variables and objective functions. The variety of solutions allows the decision-makers to better understand the consequences and benefits of choosing one solution over another while having different sets of values for each of the considered variables.

The model introduced the number of labor per task, labor experience, material quality, and resource cost as variables that make up the time and cost functions to allow decision-makers to assess the required and optimal resource assignment levels. The trade-off among the functions of time, cost, and quality was observable in the results and the overall results were robust. The model is also simple and can be easily changed to fit the project description. To validate the results of the model, NSGA II method was implemented on a project made up of 10 construction activities. Genetic Algorithm (GA) was also implemented to validate the model and provide comparison metric. The comparison between both results confirms that the model is reliable and accurate.

The size of project, availability of data, number of constraints, and method of optimization were found to be some of the critical decision variables when it comes to such models. Future works can investigate the model based on a real-life large-sized project with enough data to create a successful model. Additionally, adding more variables into the objective functions of time, cost, and quality would present more accurate and representative results.

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ABOUT AUTHORS

Dr. Kamal Jaafar is an Associate Professor at the Faculty of Engineering and Information Sciences, University of Wollongong in Dubai. He is the Program Director for the Master of Information Technology Management, Master of Engineering Management and the Master of Engineering Asset Management.

He holds BS, MPhil and Ph.D. degrees in Civil Engineering from the University of Cambridge and an MBA from the Ashcroft International Business School in Cambridge.

His research interests focus on project and construction management. His research has been published in well-known engineering journals such as the ACI Journal, Canadian Journal for Civil Engineers, and Magazine of Concrete Research.

Dr. Jaafar is a corporate consultant and a trainer in Project Management.

Prof. Mohamed Watfa is the Associate Dean (Research) in the Faculty of Engineering and Information Sciences at the University of Wollongong in Dubai. Prior to this, he was an Assistant Professor at the American University of Beirut (AUB). Email: mohamedWatfa@uowdubai.ac.ae

Prof. Watfa received his Ph.D. from the School of Electrical and Computer Engineering at the University of Oklahoma in Norman, Oklahoma, USA. Prof Watfa received the competitive UOWD Research Excellence Award which was a direct result of his ambitious research track record. He recently was chosen as the outstanding professor of the year by the Middle East PR Awards.

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