THESIS

FINDING A SOLUTION FOR THE TRADEOFF BETWEEN TIME, COST AND SUSTAINABILITY/LEED CREDITS FOR NEW CONSTRUCTION

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ABSTRACT

FINDING A SOLUTION FOR THE TRADEOFF BETWEEN TIME, COST AND SUSTAINABILITY/LEED CREDITS FOR NEW CONSTRUCTION

Project complexity generated tradeoffs in construction, which evolved over decades. This research focuses on the tradeoff between time-cost and sustainability represented in the LEED credits (Materials and Resources in particular). The research was broken down into preliminary and validation studies, wherein the preliminary study used an exhaustive search to find the optimized solution. In validation case study, the size of dataset increased exponentially, and it became computationally incompatible to find the optimized solution. Genetic Algorithm (GA) was hence used to find the optimized solution based on priority factors entered by the user. Usage of GA was validated using the preliminary study data and then applied to the validation study data. A tradeoff could be seen between the priority factors and the optimized solution. It was found that the optimization model was successful in minimizing the time and cost, concurrently maximizing the credits for a validation case study conducted for a real-life project.

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Chapter 1: Introduction

In the past two decades, the complexity of construction projects has increased with development in the latest technology, which made it difficult to deliver projects on schedule and within budget, often leading to schedule and cost overruns, and making it difficult to solve the tradeoff between time and cost (Gidado, 1996). The construction industry has been facing the most basic tradeoff between time and cost regardless of the project scale (Hegazy, 1999). This type of tradeoff was first identified in the manufacturing industry's supply chain management which is defined as "a set of three or more entities directly involved in the upstream and downstream flows of products, services, finances, and information from a source to consumer" (Mentzer et al., 2001). Altiparmak, Gen, Lin, and Paksoy (2006) determined that time and cost are affected greatly in a supply chain management and proposed the concept of optimization as the solution to that tradeoff. The tradeoffs were realized in the construction industry as well; transforming from the basic tradeoff between time and cost (Hegazy, 1999), to more complex tradeoffs (e.g. Time, cost and quality). With the increase of environmental awareness in the construction industry, the associated environmental impacts were realized and its mitigation efforts ensued in new construction (Ofori, 1992). Thus, the concept of sustainability emerged to reduce the environmental impacts in new construction and renovation projects. However, it was debated that sustainability applications weren't cost effective and projects often went over budget, as it required intense pre planning and budgeting before the start of project (Robichaud & Anantatmula, 2010). Contrarily, Langdon (2004) argued that using sustainable materials will reduce the building's cost in operation and maintenance phase. In an article in Harvard Business Review, authors stated that owners have a misplaced belief that using sustainable materials would have a negative impact on their revenue due to increasing costs (Nidumolu, Prahalad, & Rangaswami, 2009), which was contrasted by the authors' findings which suggested that cost savings can be achieved using sustainable materials and processes. Sustainability along with the previously-mentioned constraints/factors (e.g. quality) were realized to be equally important, all of which combined have metamorphosed the project's complexity, increasing the number of tradeoffs and making it harder to solve. As more projects opted for sustainable construction, the construction industry needed to rate the buildings based on standardized sustainability criteria. At the forefront, the United States Green Building Council (USGBC) came up with the Leadership in Energy and Environment Design (LEED) as a sustainability criteria rating system (Muse & Plaut, 2006). LEED is a credit based system where sustainability criteria for a building is formulated as points under the different credit sections of Location and Transportation, Sustainable Sites, Water Efficiency, Energy and Atmosphere, Material and Resources, Indoor Environment Quality, Innovation and Regional Priority. The total number of points earned by a building places it under different certification levels (certified, silver, gold, platinum) (USGBC, 2013).

This thesis is focused on the tradeoff between Time, Cost, and the sustainability criteria for the Material & Resources credits (section of the LEED checklist). The Material and Resources (MR) section of the LEED aims at reducing and minimizing the waste generated and the embodied energy associated with it. The four major waste reduction approaches as directed by the Environment Protection Agency (EPA) are source reduction, reuse, recycle, and conversion of waste to energy. The LEED MR section gives a fresh perspective on the analysis of materials through Life Cycle Assessment (LCA), which helps in comparing two products with different sustainable features. It also takes into account, the materials' manufacturing location to give an economic incentive to the companies using local materials for their projects (Cottrell, 2014).

Problem Statement

The construction industry has dealt with several tradeoffs through the past decades, some of them being: time and cost (Hegazy, 1999); time, cost and quality (El-Rayes & Kandil, 2005); Quality and Sustainability (El-Mikawi, 2005); Time, Cost, and Environment Impacts (Ozcan-Deniz, Zhu, & Ceron, 2011) etc. A change to any one of these factors may result in the change of one or more of the other project factors, typically causing cost and schedule overruns (Frimpong, Oluwoye, & Crawford, 2003; Mansfield, Ugwu, & Doran, 1994). These tradeoffs were attempted to be solved using optimization techniques that originated from manufacturing industry's supply chain management (Altiparmak et al., 2006). After a successful use of optimization in the manufacturing industry, it was promoted as a tool to solve the tradeoffs in construction. Past decades saw the evolution of tradeoffs in construction industry from basic time – cost tradeoff to complex resource-based tradeoffs. El-Rayes and Kandil (2005) used optimization to solve the tripod tradeoff in construction, between time, cost and quality. Zahraie and Tavakolan (2009) discussed the usage of specific resources for selected activities which resulted in the optimization of time and cost, with a constrained resource usage, which was later narrowed down into a more focused resource constrained project scheduling optimization problem (Kadam & Mane, 2015; Yu, Zhan, Nie, & Xu, 2009).

As discussed above, a cornucopia of tradeoffs have been encountered and resolved using mathematical optimization techniques to enable the construction and manufacturing industries in managing such complex tradeoffs. Due to a growing emphasis on sustainable buildings, owners face a dilemma over the investment decisions in achieving the desired sustainability goals while maintaining the project's budget and schedule. A study conducted in 2011 by Mapp, Nobe, and Dunbar (2011), showed that the LEED certification adds around 2% - 3% to the total construction cost and around 2% to the overall project cost. It was also found that the LEED certification process adds architecture and engineering time, in addition to the modelling costs associated (Kats, 2003). Therefore, the cost, time and sustainability (mostly represented by LEED credits), became an inseparable tradeoff that has to be addressed. In this research, only the Material and Resources category has been taken into consideration which aims to use materials with low embodied energy that helps in reducing the total energy usage in construction (Thormark, 2002).

This research directly addresses the problem faced by the owners and design-builders in solving the tradeoff between the time, cost and sustainability in construction projects. In addressing the research problem, the following research questions were developed:

1. How to solve the tradeoff between time, cost and MR section of LEED?
2. Which optimization method should be used to solve that tradeoff, and which algorithm should be used for the chosen method of optimization?
3. How to find an optimal/near optimal solution?

While answering these research questions, this study helps in providing a solution to one of the most recent tradeoffs in construction projects, represented in the tradeoff between time, cost, and sustainability. Though many aspects of the intended tradeoffs have been considered, the tradeoff between time, cost and Material and Resources section of the LEED has not been undertaken in previous research efforts. The following literature review will explore the different research efforts that have addressed similar problems and further clarify the novelty and the need of this research study. It will also clarify and address the numerous definitions and concepts used in the research study.

Chapter 2: Literature Review

This chapter examines the existing body of knowledge regarding this research topic. First, the project factors/attributes are introduced and explained, followed by the tradeoffs between them. Thereafter, the concept of optimization is introduced along with its application in solving different tradeoffs in the manufacturing and construction industry.

2.1 Project Tradeoff Factors/Attributes

Any construction project has different attributes that defines the overall project success and implementation. For the purpose of this research, the main factors that will be addressed are the cost, time, and sustainability (as related to Material and Resources) of a project.

2.1.1 Project Time/Duration

Project duration is defined in the Project Management Body of Knowledge (PMBOK) as "The number of work periods (not including holidays or other non – working periods) required to complete an activity or other project elements" (PMBOK, 1996). A more comprehensive definition by Cleland and King (1983) took the projects' life cycle into account in calculating project duration, which encompassed the total duration of the project, from the design to the closeout phase including the delays and impacts on the schedule. A project duration can be divided into construction duration and contract duration. Construction duration represents the total number of working days excluding the weekends and holidays. On the contrary, contract duration elucidates the duration defined in the contract between the owner and the contractor including all the holidays and the weekends (Williams, 2008).

The duration of a project usually changes due to external factors (i.e., unforeseen conditions) which could result in schedule overruns. The solution to manage the schedule overruns is to find the underlying causes behind the delay and mitigate these causes to preserve the overall project duration (Ahmed, Azhar, Castillo, & Kappagantula, 2002). Earlier studies have shown that location and building type did not have any effect on the duration of project (Bromilow, 1969), but was later negated by reassessment studies which proved that the location of the project can have a significant effect on project duration (Bromilow, Hinds, & Moody, 1980). Kaka and Price (1991) came to a conclusion that public buildings take longer to complete on average as compared to private buildings. Assaf, Al-Khalil, and Al-Hazmi (1995) found 56 factors causing project delays and grouped them into 8 categories as mentioned below:

1. Materials
2. Manpower
3. Equipment
4. Financing
5. Environment
6. Changes
7. Government relations
8. Contractual relationships
9. Scheduling and Controlling Techniques

Wambeke, Hsiang, and Liu (2011) defined 10 most frequent factors that cause project delays and increase project duration, the most prominent being delay in shop drawings from the engineers. Earlier studies have concluded that the reduction or preservation of the overall project duration can only happen if the durations on the critical path is changed (Arditi & Pattanakitchamroon, 2006; De Meyer, Loch, & Pich, 2002; Kelley Jr & Walker, 1959; Santiago & Magallon, 2009). However, several studies have shown that changes in duration of non – critical activities have compound effects. For example, increasing the duration of non – critical activities leads to cessation of resource utilization pattern which leads to a high risk potential for schedule overruns and negative impacts on the project cost (Harris & Ioannou, 1998; Ipsilandis, 2007). Decreasing the duration of non - critical activities could also increase the float which could be used by the General Contractors in case of delays, thus reducing the risk of schedule overruns within the total project duration (Al-Gahtani & Mohan, 2005). Cost overruns are closely associated with schedule overruns, where the impact of schedule overrun directly affects the project cost (Kaliba, Muya, & Mumba, 2009).

2.1.2 Project Cost

The Construction Management Association of America (CMAA) defines the project cost as “All costs attributed to the construction of the project, including the cost of contracts with the contractor(s), construction support items, general condition items, all purchased labor, material and fixed equipment” (CMAA, 2010). Similar to the project duration, project costs can be divided into several categories/types. Epstein and Maltzman (2013) defined types of costs associated with a project as:

1. Fixed Costs
2. Variable Costs
3. Direct Costs
4. Indirect Costs
5. Sunk Costs

Fixed costs are one-time costs incurred in a project in execution of an important purpose (Epstein & Maltzman, 2013). Wang and Yang (2001) iterates that the fixed costs do not show any changes with variation in the quantity. Insurance and legal bills are some examples of fixed costs (Pettinger, 2017). On the contrary, variable costs are incurred over a period of time such as hiring skilled labor or renting a crane which will vary with increase or decrease in quantity production (Epstein & Maltzman, 2013; Wang & Yang, 2001). Costs of materials, labor, management etc. which are incurred directly on a company towards execution of a project, is known as direct costs (Epstein & Maltzman, 2013). Indirect costs on the other hand are not culpable directly to the project (e.g. lighting, temporary facilities, etc…) but they are still needed for project execution (Epstein & Maltzman, 2013). In addition, Liljas (1998) categorized "absence from paid work" and "reduced productivity at work", as components of the indirect cost. Sunk costs are considered losses already incurred on a project and which cannot be recovered (Epstein & Maltzman, 2013). For example, capital already spent on a project is considered as sunk costs, as it's irrecoverable (DeBenedetti, 2015). Regardless of the cost types, cost overruns can happen on any project as a result of the variability in any of these types.

Cost overruns are defined as, "the amount of money required to construct a project over and above original budgeted amount" (Kaliba et al., 2009). A study conducted by Christensen (1994), showed that 64% of completed defense projects ran into cost overruns. Another study showed the increasing trends of cost overruns (mostly doubled) in government infrastructure projects (Edwards & Kaeding, 2015). A construction industry wide survey conducted in early 1990s suggested that 33% projects experienced cost overruns (Barrick, 1995). Similar pattern of cost overruns observed in the following years, where the percentage of dissatisfied construction clients reached 60%, due to cost overruns (Jackson, 2002). The majority of cost overruns may occur before the start of a project due to modification of the estimates or inflation (Kaliba et al., 2009). Projects in remote locations are more prone to cost overruns as the cost of attracting, training and retaining labor (including training and transportation cost among others) is very high

(Jergeas & Ruwanpura, 2009). Kaliba et al. (2009) defines certain factors that leads to project cost overruns:

1. Size of a project
2. Project scope enlargement
3. Inflation
4. Length of time to complete the project
5. Incompleteness of preliminary engineering and quantity surveys
6. Engineering uncertainties
7. Exogenous delays
8. Complexities of administrative structures
9. Inexperience of administrative personnel

Cost overrun is considered a global scale challenge. In Nigeria, cost overruns are mostly attributed to finance and payment arrangements, poor contract management, materials shortages, inaccurate estimating and overall price fluctuations (Mansfield et al., 1994). A similar study was conducted in Ghana for groundwater projects in which 26 causes were determined from a questionnaire survey, the top 5 being (Frimpong et al., 2003):

1. Monthly Payment Difficulties
2. Material Shortage
3. Material Procurement
4. Obtaining materials at current prices
5. Financial Difficulties of Contractor

An Indonesian study for high rise construction projects showed that the cost overruns were associated with inaccuracies of quantity takeoff, inflated cost of materials and cost increase due to environmental restrictions. However, on the scale of severity, inflated material cost ranked the highest followed by inaccuracies in quantity takeoff and cost increase due to environmental restrictions (Kaming, Olomolaiye, Holt, & Harris, 1997).

Due to the evolvement of sustainable construction, buildings are now evaluated with the perspective of not just immediate construction cost, but the life cycle cost. Life Cycle Costs (LCC) can be defined as "the summation of cost estimates from inception to disposal for both equipment and projects as determined by an analytical study and estimate of total costs experienced during their life" (Barringer, Weber, & Westside, 1995). LCC takes into account differing initial costs, operating costs and maintenance costs. A LCC analysis of a building predicts the costs incurred through the acquisition, design, construction phases, along with the building's maintenance, demolition or rehabilitation. A brief overview of all the different costs associated with the LCC, can be summarized as in the following (Buildings, 2005):

1. Utility Cost: Energy utilities such as gas and electric, and non-energy utilities like water and sewer service, are associated with utility costs.
2. Maintenance Cost: Costs associated with maintaining the building functionality.
3. Service Cost: Costs associated with daily activities such as janitorial services, pest control and maintenance of the elevator are some of the examples that falls under the service cost category.
4. Remodeling Cost: This cost may/may not be included in the LCC analysis of the building depending on the project team choices and scope of work.

5. End- of- life Cost: The residual value of the building and the demolition or rehabilitation costs are included in this section.

2.1.3 Sustainability

Sustainability came into the picture as a result of adverse effects on the environment due to construction activities such as using harmful/polluting materials and non-renewable energy sources that contribute to the increase of greenhouse gas emissions. The United States Environmental Protection Agency (EPA) defines sustainability as a method to "create and maintain the conditions under which humans and nature exist in productive harmony to support present and future generations" (EPA, 2011). Sustainable construction can also be defined as constructing cost effective facilities in a way that preserves the environment and adds to the environmental and social value of the community (Halliday, 2008). According to a US survey by Augenbroe, Pearce, Guy, and Kibert (1998), 50% of nation's wealth is attributed to buildings, which emphasizes the need of sustainable design that can save money, increase efficiency and most importantly, reduce the environmental impact of the construction industry. The widespread use of sustainable design demanded the development of rating and certification systems to rate the buildings' sustainability. Some of these systems as defined by the US Green Building Council (USGBC) are Leadership in Energy and Environmental Design (LEED), Green Globes, The Living Building Challenge (LBC), and WELL. Among all, LEED is the most widely used system in US. As previously mentioned, the LEED MR section is the main sustainability criteria in this research study and it is discussed in detail in the following section. The Green globes accreditation body was founded in 2002, and is managed by the Green Globes organization (Globes, 2009; Smith, Fischlein, Suh, & Huelman, 2006). It is an online certification tool for green buildings, which could be used for a new construction, commercial interiors and existing buildings.

Interactiveness, flexibility and affordability are some of the major attributes possessed by green globes rating system. Green globes takes into account categories such as project management, site, energy , water, materials and resources, emissions and indoor environment (Globes, 2009). Living Building Challenge (LBC) is another rating system that was founded by the International Living Future Institute in 2011 with the goal of “transforming how we think about each act of design and construction as an opportunity to positively impact community of life and cultural fabric of human communities” (McLennan, 2006). LBC considers several categories such as type of place, water, energy, health and happiness, materials, equity, and beauty. WELL building standard was introduced by the International WELL building institute in 2013 (WELL, 2018). The WELL certification standard and rating systems focuses on health and wellness of building occupants considering around 100 performance metrics and requires on-site assessment by a third party (WELL, 2018). WELL has 8 different categories namely air, water, nourishment, light, fitness, comfort, mind and innovation as the grounds for certification (WELL, 2018).

2.1.3.1 Leadership in Energy and Environment Design (LEED)

According to USGBC, LEED version 2009 has different certification levels based on the points obtained by the building in the sustainability metric’s categories. There are 8 overall categories in the LEED certification system. The following are all the categories with the possible points per category:

1. Location and Transportation [16 credits]
2. Sustainable Sites [10 credits]
3. Water Efficiency [11 credits]
4. Energy and Atmosphere [33 credits]
5. Material and Resources [13 credits]

6. Indoor Environmental Quality [16 credits]
7. Innovation [6 credits]
8. Regional Priority [4 credits]

Each category has a possible set of earned points and the total points corresponds to the certification level a building can attain. There are four LEED certification levels as in the following: (1) Certified (40 to 49), Silver (50 to 59), Gold (60 to 79) and Platinum (80 to 110).

2.1.3.1.1 Location and Transportation

This category pertains to the building location, the nearby facilities & amenities available, the surrounding environment, and the modes of transportation available to the building's residents. Several credits have been dedicated to promote biking and green vehicles in order to reduce environmental pollution and promote green transportation such as low carbon emission vehicles, electric automobiles, bicycles etc. (USGBC, 2013).

Few points are also dedicated to reduce the parking footprint in and around the buildings. As logic dictates, the lesser the number of cars owned/parked by the residents, the lesser the parking footprint. In applying these credits, some countries like Taiwan have made changes to the most used mode of transport (Motorcycles in their case), replacing them with a greener and low carbon emission options to earn Green Vehicles credit in an effort to reduce carbon emissions by 50% of the 2005s level (Trappey et al., 2012). In another effort to curb pollution, residents in California were asked if they would prefer more taxes and fees for those people whose vehicle contribute to a higher degree of pollution, to which more than 50% of the California residents agreed (Agrawal, Dill, & Nixon, 2010).

2.1.3.1.2 Sustainable Sites (SS)

This category focuses on preserving the environment around the building, restoring the regional ecosystems and preserving the biodiversity. It ensures that new construction has minimal impact on the existing ecosystems by assessing the site, very early in the project cycle, to avoid any harm to the habitats and water resources near the site (Kibert, 2016).

2.1.3.1.3 Water Efficiency (WE)

Water efficiency (WE) focuses on reusing and conserving water. The main aim of this category is to reduce water waste and promote creative reuse techniques in the community. A major part of US energy usage goes into wastewater treatment which could be reduced by efficient use of water and by keeping waste to a minimum (USGBC, 2013).

2.1.3.1.4 Energy and Atmosphere (EA)

This category recognizes the reduction in the usage of conventional sources of energy (fossil fuel) which increase the greenhouse gas concentration in the atmosphere. It encourages the use of renewable energy sources and lowering the energy needs by adopting passive design strategies, while achieving an optimal thermal comfort (USGBC, 2013).

2.1.3.1.5 Material and Resources (MR)

USGBC (2013) defines the MR section scope as “to reduce waste generated by the building occupants that is disposed of, in landfills”. Disposing of waste in landfill is unsustainable as it generates methane gas (greenhouse gas) (Read, Hudgins, & Phillips, 2001). Converting waste into energy can reduce the amount of waste directed to landfills and offset the energy needs from the primary units, and reduce the greenhouse emissions (Psomopoulos, Bourka, & Themelis, 2009). The major aim of this category is to use materials with low embodied energy that helps in reducing the total energy usage in construction (Thormark, 2002). Mostly, materials pertaining to permanent installations in a building are considered in the Materials and Resources category of LEED (Cottrell, 2014).

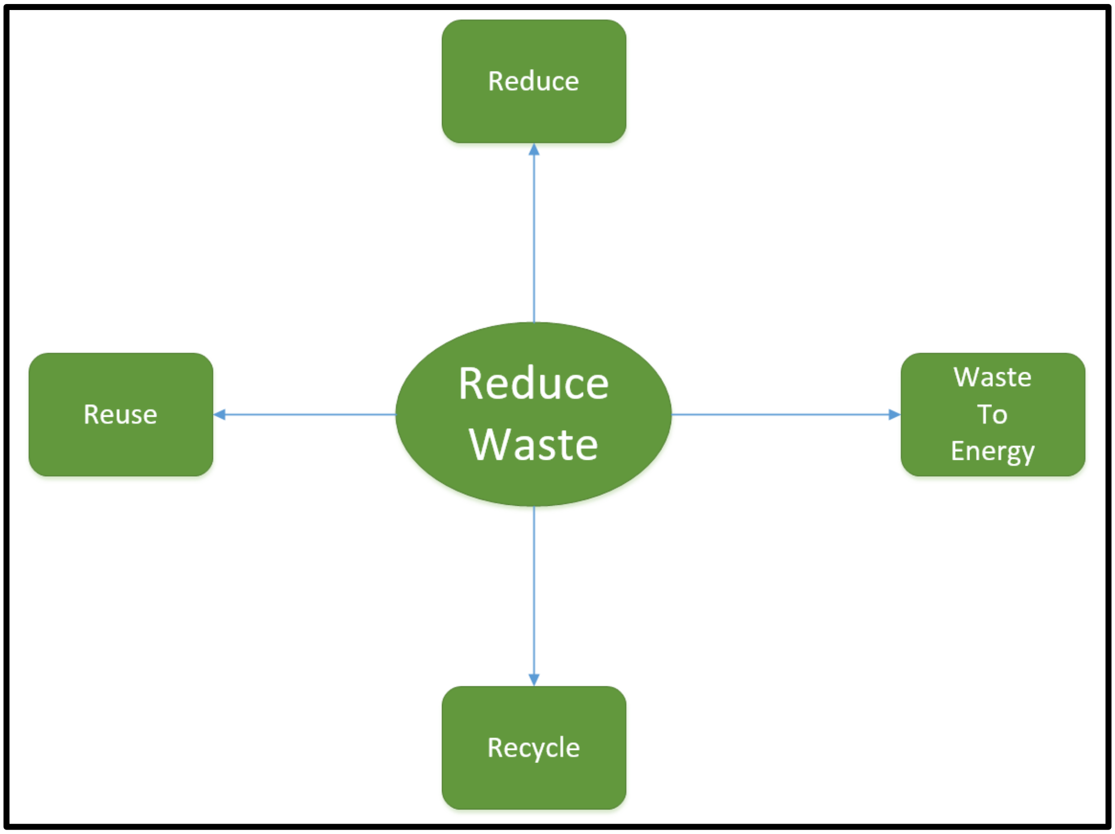

Figure 1: Modus Operandi of Waste Reduction (Cottrell, 2014)

According to Cottrell (2014), reducing, reusing, recycling and conversion of waste into energy are four major approaches for waste management as shown in figure 1. Reduction at source helps in reducing the life cycle cost, reusing the products helps reduce the greenhouse gas emissions, and recycling helps converting waste into reusable material. The materials which cannot be recycled can be transformed into energy to reduce the waste going into landfills. The MR LEED credits which have been considered for the purpose of this research due to data constraints are as in the following:

1. Recycled Content

2. Regional Materials
3. Rapidly Renewable Materials

2.1.3.1.5.1 Recycled Content

These credits focus on reducing the environmental impacts associated with the use of materials by choosing materials with more recycled content. The sustainable value for recycled content is calculated by summing up the pre-consumer and ½ of the post-consumer recycled content percentages, all in terms of cost. Pre-consumer materials can be reused from the feedback loop of supply chain's end product and post-consumer materials cannot be reused. A sustainable criteria value up to 10% of total cost earns 1 credit and 20% or more earns 2 credits (USGBC, 2013).

2.1.3.1.5.2 Regional Materials

These credits aim to reduce the environmental impacts by using materials that are manufactured locally, in order to reduce the associated cost of transportation and greenhouse emissions. For LEED 2009, the materials are considered regional if they are extracted within 500 miles of the project location. According to USGBC (2013), the total distance of the materials from the point of manufacture to the project site is calculated using equation 1:

$$\left({}^{Distance\ by\ rail}\!/_{3} + {}^{Distance\ by\ inland\ water}\!/_{2} + {}^{Distance\ by\ sea}\!/_{15} + Distance\ by\ all\ other\ means \right) \leq 500\ miles$$

Equation 1: Total Travel Distance Calculation

If 10% of total cost of materials are regionally extracted, then 1 credit is awarded and 2 credits are awarded for 20% or more of total material cost (USGBC, 2013).

2.1.3.1.5.3 Rapidly Renewable Materials

These credits focus on selecting materials which can be replenished with higher frequency, so that the usage of materials does not impact the ecosystem negatively. It is expected that the rapidly renewable products are manufactured/harvested under 10 years cycle and 1 credit is awarded if the cost of rapidly renewable materials is more than 2.5 % of the total cost of materials (USGBC, 2013).

2.1.3.1.6 Indoor Environmental Quality (IAQ)

The IAQ category addresses the air quality along with the physical and mental comfort of the building occupants. It aims at improving the occupant comfort level to have better productivity at work and good health. Passive design strategies promoting thermal comfort and developing areas for recreational activities are some ways of improving the indoor environmental quality (USGBC, 2013).

2.1.3.1.7 Innovation

This category considers all the innovative techniques developed in construction of a sustainable building. New and improved techniques to improve passive designs or reduce the embodied energy are some of the examples in this category (USGBC, 2013).

2.1.3.1.8 Regional Priority

This particular category aims at preserving the environment as related to a specific region. The metric for calculating the credits for this category may change from one region to another as different regions may have different requirements for environmental preservation (USGBC, 2013).

In this research study, only the Materials and Resources category for LEED 2009 has been taken into consideration.

2.3 Tradeoffs

These aforementioned project cost, time and sustainability factors, do not work individually, instead, all of these or some in pairs, give rise to tradeoffs which makes the decision making with respect to their prioritization, very difficult. These tradeoffs can be in many forms such as time- cost trade off, cost- quality trade off, time- cost- quality trade off, or a time-cost-quality-sustainability trade off, etc. Figure 2 represents The Iron Triangle followed by researchers in the past, as a framework to demonstrate a balance between the time, cost and quality (Atkinson, 1999). It works on the analogy that if one side of the triangle is changed, then the other two sides would be modified in accordance with the change. The decisions related to these tradeoffs are usually based on the project stakeholders' priorities.

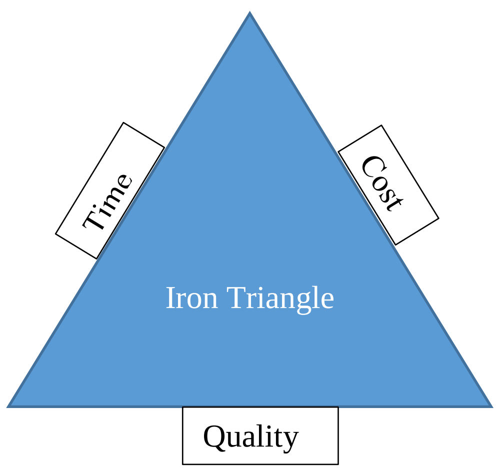

Figure 2: The Iron Triangle

Higher quality of construction materials often increase the cost and duration of resources' procurement due to the difficulty in procurement of rare and high quality materials (Sambasivan & Soon, 2007). The construction cost corresponds to the cost of resources (people, materials, equipment and working capital) and cost overruns are often associated with resources unavailability (Naik & Kumar, 2013). Sonmez, Iranagh, and Uysal (2016) pointed out that the resources for all construction projects are constrained. Thus, construction managers and superintendents are always faced with a dilemma of optimum resource utilization based on the tradeoff between time, cost and quality (Afshar, Kaveh, & Shoghli, 2007; El-Rayes & Kandil, 2005). El-Rayes and Kandil (2005) combined construction method, crew formation and crew overtime policy (decision variables having significant impacts on time, cost and quality), into a resource utilization variable, and concluded that quality is dependent on the resource utilization options. Some of the existing techniques of time- cost- quality optimization are mathematical models, heuristic methods and global search algorithms (Yang, 2009). Ahari and Niaki (2013) classified the time- cost- quality tradeoff problem as a multi- objective optimization problem to optimize multiple objective functions at the same time, subject to a set of constraints. The multi-objective decision making technique had the capability of solving the three dimensional tradeoff of time-cost and quality (El-Rayes & Kandil, 2005).

This dilemma of prioritizing different project factors can be solved using mathematical optimization methods that can maximize or minimize project factors, according to the project needs. The next section discusses the basic concepts of optimization, its need in solving multiple objectives with different priority factors, and the different areas where it has been used before, followed by a brief discussion on using optimization in solving the different tradeoffs in construction projects.

2.4 Optimization

Optimization is a mathematical method to maximize or minimize certain values/set of variables within a set of constraints to determine the best solution, among a pool of choices (UWASH, 2015). In mathematical optimization, a mathematical function is formulated and minimized or maximized depending on the required logic. The result obtained after a certain number of iterations would be the best possible minimum or maximum value, also known as the

Optimum value for the variable (Boyd & Vandenberghe, 2004). Deb (2014) (page V), defined the Optimization as "the task of finding one or more solutions which correspond to minimizing or maximizing one or more specified objectives, and which satisfy all constraints (if any)."

Optimization can also be used for multiple objectives that need to be maximized or minimized at the same time which requires a different approach than a single objective optimization problem. The multiple objectives can be optimized using "Multi-Objective Optimization" which takes into consideration several contrary objectives. The multi-objective optimization solution is not a single optimal value, instead, a set of optimal values are obtained among which there is a tradeoff (Deb, 2014). Optimization, however, is not a new technique, but has existed since ancient times as discussed in the following section.

2.4 History of Optimization

The earliest work of optimization can be traced back to Greek Mathematicians when Euclid considered the minimum distance between a point and a line in 300 BCE (Cha, 2007). In 100 BCE, Heron proved that light travels between two points through the path with shortest length when reflecting from a mirror (Jenkins & White, 1957). Isaac Newton and Leibnitz created the calculus of variation which opened doors to finite optimization problems (Bertsekas, 1982). In 1784, G. Monge investigated one of the first combinatorial optimization problems known as the transportation problem (Schrijver, 2005). The 19th century saw the advent of first algorithms presented by Weierstrass, Steiner, Hamilton and Jacobi which further developed the calculus of variation (Grosholz & Breger, 2013). In 1826, Fourier formulated the Linear- Programming method to solve problems in mechanics and probability theory. By the 1870s, the works of Walras and Cournot made optimization an integral part of the economic theory (Novshek & Sonnenschein, 1978). In the 20th century, the calculus of variation was further developed by Bolza, Caratheodory, and Bliss while Hancock published the first book on optimization, "Theory of Minima and Maxima" in 1917. After World War II, optimization techniques rapidly developed with operational research. In 1944, Von Neuman used the idea of dynamic programming which works on the principle of breaking down a big problem into smaller subsets of problems and solving them. The solution subsets would be stored in the memory and could be used in the future if encountered by a similar problem subset (Backus, 1978). In 1951, Kuhn and Tucker invented optimal conditions for nonlinear problems (Kuhn, 2014) and by the 1980s, the heuristic algorithms for global optimization and large scale problems were developed as computers became more efficient in computation capabilities (Mandl, 1980). After 1990s, complex algorithms were developed and used in the optimization process thereafter (Kiranyaz, Ince, & Gabbouj, 2014). The first widespread application of optimization was in the manufacturing industry.

2.4.1 Optimization in the Manufacturing Industry

One of the early major problems encountered by the manufacturing industry was to "schedule scarce resources among different manufacturing demands" (Cai & Li, 2012). This required an optimization of the resources' distribution among the different projects to ensure efficient utilization of the capital invested in these resources during the manufacturing process (Cai & Li, 2012). After 1980s, automation was required in supply chain management due to the increased product demands when Ascheuer (1995) used optimization to minimize the loading and unloading times of automated storage systems. In the 21st century, the technology became more advanced, and the market grew further due to the higher demands, all which required different methods to solve a larger scale problem.

Chen and Lee (2004) incorporated another variable factor i.e., price and used multi-objective optimization of supply chain networks with uncertain product demands and prices.

Altiparmak et al. (2006) solved a non- linear programming model for multi- objective optimization of Supply chain network design by using genetic algorithm to minimize cost and maximize customer service and capacity utilization, as the three main objectives. Pishvaee, Rabbani, and Torabi (2011) devised a robust optimization approach to a "closed- loop" supply chain network design under the uncertainty of fluctuation demands in different markets.

Lagging behind the manufacturing industry, the optimization technique had been utilized in the construction industry to solve major tradeoffs and optimize resource utilization.

2.4.2 Optimization in Construction Industry

Optimization was introduced in the construction industry to solve different tradeoffs that overburdened the decision making process. Quality is one of the most difficult factors to quantify; El-Mikawi (2005) prioritized factors based on information from construction site (provided by project manager/superintendent), to calculate the quality of a project. Time and cost constraints in any construction project are closely associated with the utilization of resources. Resource utilization is a critical constraint for optimizing the time and cost in construction projects and avoid delays and cost overruns (Christodoulou, Ellinas, & Aslani, 2009). Lucko (2011a) emphasized the need for smart resource modelling into linear scheduling to enhance resource utilization efficiency in repetitive operations. Several scholars have used Genetic Algorithm as the computational technique to solve resource constrained problems and others used it with local search and hyper heuristic techniques (Anagnostopoulos & Koulinas, 2010) to solve resource constrained problems.

In solving these aforementioned tradeoffs, Genetic Algorithm (GAs), Particle Swarm Optimization, Simulated Annealing, Ant Colony Optimization, and Artificial Neural Networks (ANNs) were some of the different programming algorithms used to solve the different optimization problems in construction. These programming algorithms require a large amount of data input, pertaining to the variability of the tradeoffs, and going through a number of iterations to reach the final result represented in a set of optimal values.

2.4.2.1 Time – Cost – Quality Optimization

Though the priority level of the project factors (time, cost and quality) usually depends on the superintendent and the project manager as decision makers, optimization techniques can help in determining the optimum values for the time, cost and quality of construction project.

Atkinson (1999), used optimization to solve the tradeoff between time, cost and quality by maximizing the Quality function and Minimizing the Time and Cost functions to increase the project quality and lower the cost and duration. Lucko and Su (2014) used singularity functions to minimize the cost and time, and maximize the quality. Afshar et al. (2007) emphasized the importance of optimization of time, cost and quality as related to the new types of contracting techniques using the Ant colony optimization algorithm to find an optimal solution. A better approach to time-cost-quality optimization was developed by El-Rayes and Kandil (2005) focused on effective utilization of resources while optimizing the three project factors. El-Rayes and Kandil (2005) tried several resource options to calculate the duration and cost associated with each option, and measured the quality performance for each resource option using Genetic Algorithm to solve the three dimensional tradeoff problem. After addressing the tradeoff between time, cost and quality, resources began to be seen as a decisive aspect which could drive the duration and cost of a project. The next section focuses on optimization with a special orientation towards resources.

2.4.2.2 Resource Oriented Optimization

Much research has been done in resource optimization to find the most efficient resource utilization solution and minimize the cost of construction projects (Zahraie & Tavakolan, 2009). A variety of methods have been used to optimize resources, using mathematical modelling and computer algorithms. The resource constrained project scheduling problem by Wall (1996) with the main objective to minimize the project duration, is one of the most prominent (Yu et al., 2009). Meta heuristic methods were also seen to be the best fit for finding an optimal solution for the resource optimization problem (Rajeev & Krishnamoorthy, 1992). Yu et al. (2009) used the Genetic Simulated Annealing Algorithm (GSA) for solving the resource constrained project scheduling problem with the objective of minimizing the project duration using genetic algorithms in combination with simulated annealing to "improve the local searching performance and boost up evolution capability". Kadam and Mane (2015) used a Genetic Algorithm with a local search technique to find the optimum solution, based on the principle of limited resource allocation to different activities. Lucko (2011b) used singularity functions for financial modelling and optimization of resource utilization.

Tseng and Chen (2009) solved the multimode resource constrained project scheduling problem (MRCPSP) for a very high number of iterations using two-phase genetic local search algorithm. MRCPSP type problems are categorized as a Non deterministic polynomial- time hard (NP – hard) problem, subject to constraints on the activity precedence and the limits of resources. The genetic local search algorithm was used to run different modes of execution with varying associated costs, in order to come up with minimum duration of project. The modes of execution were compared to determine the one with least cost and duration.

Anagnostopoulos and Koulinas (2010) used leveling priorities to level resources, followed by generation of random networks and usage of hyper – heuristic genetic algorithm to determine the network with least duration. Cai and Li (2012) observed that most research efforts were directed to optimize and distribute resources in a single project and considered a broader view of resources being distributed among multiple projects. Sonmez et al. (2016) combined both the techniques of optimization of resources and the time- cost trade off problem under one umbrella and named it as the Resource Constrained Discrete Time- Cost Tradeoff Problem (RCDTCTP).

Other aspects of tradeoff in construction have been also addressed such as contracting optimization. The contracting optimization problem is addressing the issue of optimizing the project to contractor selection during the contracting stages as different contractors might have different capacities of building projects. Assigning a complex project to a small contractor might result in low- quality product and assigning an easy project to a big contractor might be underutilizing their potential. Hence mathematical modelling and optimization was used to assign construction jobs according to the contractors' capability while minimizing construction costs (Ngowtanasuwan, 2013).

The literature has shown that there have been tremendous research efforts in using different optimization methods to solve the time-cost, time-cost-quality, resource constrained time-cost tradeoffs, but the tradeoff between time, cost, and sustainability factors hasn't been thoroughly addressed. This research focuses on solving the tradeoff between time, cost and sustainability represented in the LEED MR credits. The next section discusses the methodology of tackling this tradeoff problem.

Chapter 3: Methodology

The literature review established the foundation of the scholarly research done in this study, and also uncovered the gap that this study is aiming to address. The main research problem as stated in the introduction section, was to solve the tradeoff between time, cost and sustainability (MR section of LEED credits). The methodology opted to solve the research problem is shown in Figure 3.

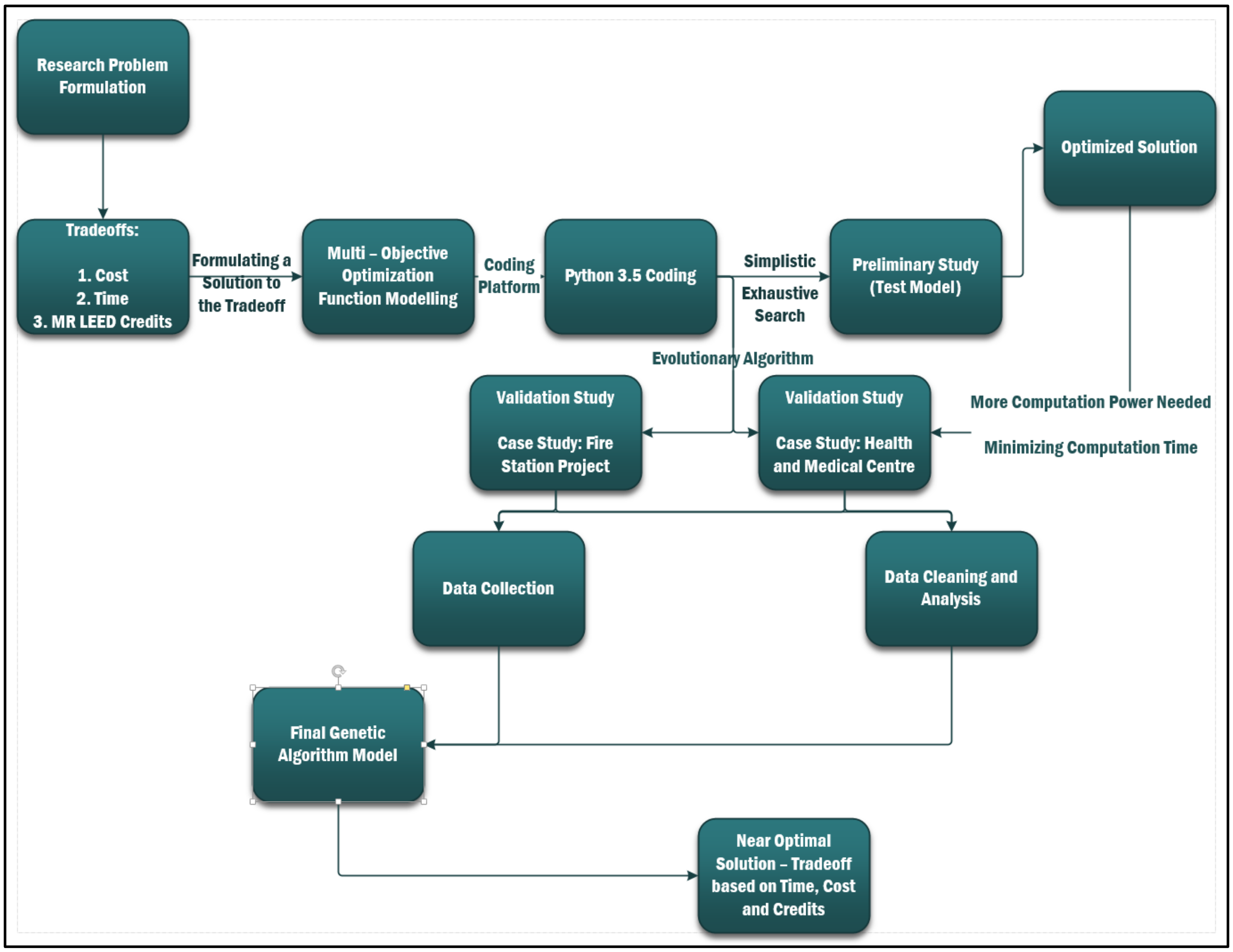

Figure 3: Methodology Map

As shown in figure 3, the research problem was formulated to solve the tradeoff between time, cost and sustainability through the presented methodology. This particular tradeoff was categorized as a multi-objective optimization problem (discussed in the following section) and the underlying procedure is developed using the optimization category. Being a multi-objective optimization problem which needs fast computing methods to evaluate multiple objectives and combinations, Python 3.5 was used as the programming language for coding the multiple objective methodology. Testing the model code (in Python) started with running a preliminary set of data through an exhaustive search and finding the optimal solution based on the user entered priorities for time, cost and sustainability (LEED MR). It was realized that the exhaustive search would be highly inefficient for higher number of combinations and therefore, evolutionary algorithms (GAs) were introduced to significantly reduce the computational time. Two validation "real world project" case studies were introduced to validate the GA optimization model. Data collection and analysis of the case study was conducted on a LEED certified project as the case study. The analyzed data was run on the code created in Python using the GA optimization model, to find the near optimal solution based on the user-defined priorities. The second validation case study was introduced to check the reliability of the optimization model and check for coherence in results when applying the optimization model to various types of projects. Each of the step explained and illustrated in Figure 3 are discussed in detail in the following sections.

3.1 Research Problem and defining Tradeoffs

The research problem was formulated based on the observed need in the literature review which resulted in identifying the tradeoff between time, cost and MR LEED credits (as defined in version 2009). Figure 4 shows a graphical representation of the research problem and the associated tradeoffs. It shows that any project has associated activities which could be executed in various ways or using different materials. For every combination of materials, there is an associated time, cost and MR LEED credits. In this research, the MR LEED credits will include the recycled content, regional materials and rapidly renewable materials.

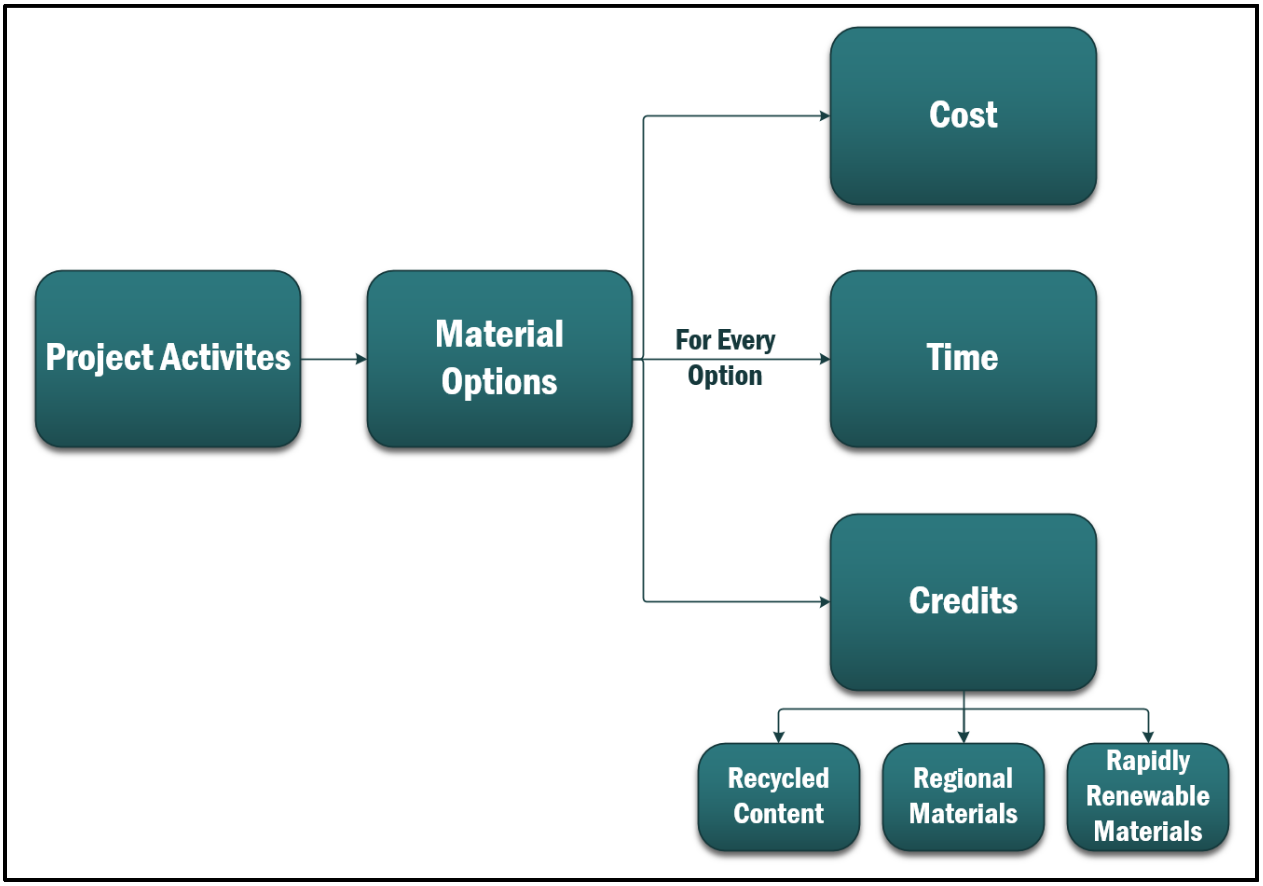

Figure 4: Research Problem and Tradeoffs

3.2 Formulating the tradeoff solution

In answering the research questions in the problem statement, and with the input acquired from the literature review, optimization techniques were ascertained to be the best answer to analyze and solve the tradeoff between time, cost and sustainability (MR section of LEED. In particular, this optimization problem can be categorized as a Multi-Objective Optimization problem which is one of the many Optimization techniques discussed below (Gropp & Moré, 1997):

1. Continuous Optimization Vs Discrete Optimization: Models that take on integer values for the variables are known as discrete optimization problems as they take on some specific set of values as the domain. Continuous optimization on the other hand, takes all real values for its variables.
2. Unconstrained Optimization Vs Constrained Optimization: Constrained optimization problems are bound by the set of constraints on the variables and an unconstrained optimization has variables that can range to infinity.
3. None, One or Many Objectives: In "none" objective optimization, the feasible solution is usually found with no objectives, meaning the user finds a feasible region in which the solution may be present without any variables being minimized or maximized. Most optimization problems however, are single objective which aim at either maximizing or minimizing the objective function based on a set of constraints. The most complex optimization among these three is the multi objective optimization which aims at both minimizing and maximizing the objective function, mostly in the case of tradeoffs.
4. Deterministic Optimization Vs Stochastic Optimization: When one has an accurate set of data, then the deterministic optimization technique is applied however, in case the data is unpredictable or uncertain, the stochastic optimization technique is applied which includes robust optimization methods.

This research's optimization problem is a multi-objective optimization problem which aims to solve the tradeoff between time, cost and sustainability (LEED MR Credits), by minimizing time and cost, and maximizing the credits.

3.3 Criteria Modelling

Modelling of a multi-objective function proceeds with the problem characterization, where the mathematical functions were formulated for each project factor and constraints were defined. This optimization problem has three different aspects of maximizing and minimizing elements. The number of credits for the Materials and Resources section of the LEED system had to be maximized while the material cost and Duration Associated with Materials (DAM) had to be minimized. The multi-objective optimization technique provided a set of optimal values as a tradeoff between the different objectives (Cover & Van Campenhout, 1977). In case of combinatorial optimization problems, as in this research problem, it was unfeasible to have a single optimal solution and hence a pragmatic way comprising of a set of optimal solutions was taken into consideration (Gropp & Moré, 1997; Konak, Coit, & Smith, 2006). Objective functions for each of MR Credits, DAM, Material Cost and MR Credits was formulated in equation 2, equation 3 and equation 4, respectively.

The maximized number of credits is described as a function of C, as shown below:

Maximize Credits:

$$F(C) = C_0 + C_1 + C_2$$

Equation 2: Calculation of Total Credits

Subject to constraints:

$$0 \leq C_0 \leq 2$$

$$0 \leq C_1 \leq 2$$

$$0 \leq C_2 \leq 1$$

F(C) = Function of Credits

C_0 = Recycled Content

C_1 = Regional Materials

C_2 = Rapidly Renewable Materials

Function of credits F(C) can be expressed as a summation of C_0, C_1 and C_2, which ranges from 0 to 2, 0 to 2 and 0 to 1, respectively. These credits are determined based on the normalized value of recycled content, regional materials and rapidly renewable materials, all of which are based on the total material cost (discussed in detail in the literature review).

The function of DAM is minimized as shown below:

Minimize DAM:

$$\sum_{\substack{i=1 \\ j=1}}^{\substack{i=m \\ j=n}} T_{i,j}$$

Equation 3: Total DAM

$T_{i,j}$ = DAM for each material option

where i represents the activity, j represents the different material options, m is the upper limit for total number of activities and n is the total number of material options per activity. The DAM function takes into account the total duration associated with completing each activity using a particular material option in the project. The duration for each material option is computed separately, which is referred to as “DAM” in this research; multiple DAMs are calculated for each activity. These are then added together (one DAM per activity) to find the total duration, which is referred to as total DAM in this research, hence working on an assumption that all activities are critical and consecutive in this project. Some activities out of the total activities under consideration would be critical according to the construction schedule, hence reducing the duration of these critical activities can reduce the project duration. However, as concluded from the literature review, reducing the duration of non – critical activities (as part of the original schedule) can reduce the project risk and increase the buffer time and floats that can be used when a delay occurs. Thus, any reduction in the DAM would in turn benefit the project either by reducing the overall project duration or by risk reduction. Similar to the DAM function, the cost function which is dependent on each of the material options used for every single activity, needs to be minimized.

Minimize Cost:

$$\sum_{\substack{i=1\\j=1}}^{\substack{i=m\\j=n}} \left[M_{i,j}\right]$$

Equation 4: Total Cost

$M_{i,\,j}$ = Material Cost of Activity

Where i represents the activity, j represents the different material options for each activity, m is the upper limit for total number of activities and n is the total number of material options per activity. Material costs is used to find the total cost of the project. Equations 2, 3 and 4 explained the process of computing the three factors of the project, which have a tradeoff among them. To solve the tradeoff using multi-objective optimization process, it is essential to have a single number that takes into account minimizing of time and cost, and maximizing of credits. This is done using a Fitness Function, which is an encapsulation of all the project factors (time, cost and LEED MR Credits) into one equation. Within the fitness function, relative Importance Factors (RIFs) are introduced to define the priority for the project factors based on the user input. These RIFs are introduced as weights for the different factors in the fitness function. A fitness function is formulated to combine the three project factors into a single number using equation *5*. Each of the variables, including the weights, are normalized.

$$Fitness\ Function = -\left(Normalized\ Total\ time\ \times \left(\frac{Wt}{Wt+Wc+Wcr}\right)\right) - \left(Normalized\ Total\ Cost \times \left(\frac{Wc}{Wt+Wc+Wcr}\right)\right) + \left(Normalized\ Total\ Credits\ \times \left(\frac{Wcr}{Wt+Wc+Wcr}\right)\right)$$

Equation 5: Fitness Function

Wt: The Relative Importance factor (RIF) for DAM,

Wc: The Relative Importance factor (RIF) for Cost,

Wcr: The Relative Importance factor (RIF) for Credits

All the variables in equation 5 are normalized, which is important to maintain the consistency of dataset by making all numbers to fall in a range of 0 to 1. This makes it easier for the GA to run on the dataset without biases. The RIFs in equation 5 are defined by the decision maker or the model user (e.g., General Contractor, LEED consultant, etc.). The option with the highest fitness value is considered the optimal solution. This is because of the fact that if positive numbers are arranged in a descending order, the negation of the order makes them in ascending order. Hence if the maximum fitness value is taken into consideration, the negative signs in the Fitness function achieves minimizing the DAM & Cost, and the positive sign achieves maximizing the credits.

3.4 Python Coding

The mathematical modelling of the Multi-Objective criteria is done using a Python 3.5 computer programmed code. Python is a higher level programming language which is user friendly and the syntax allows programmers to express concepts in fewer lines of code, compared to C and C++ (Van Rossum, 2007). Coding the model starts with import of an Excel based data set, on which the mathematical operations are performed. One of the major reasons for selecting Python as the primary programming language in this research study, is the user friendliness nature of the syntax. Python syntax includes Jupyter notebook as the editor for coding and running the model, Numpy package to create the Multi – Objective model, and panda package to import the data set from excel.

3.5 Preliminary Study

A dummy data set is prepared to serve as data source for the preliminary study which was used to test the mathematical model capabilities and functions. The preliminary study data consists of a six activity project with 3 material options to execute each activity, making a total of 3^6, i.e., 729 combinations for the total project activities' execution. The small data set is used to find a set of optimal solutions by using an exhaustive search, as part of the preliminary study. This is accomplished using Python 3.5 platform, as described in the section above. The preliminary study Python code can be referenced in Appendix A – Code for Preliminary Study. Each method of execution (in the 6 activity set) has a material cost, DAM, and a sustainable criteria value for its recycle content, regional content and rapidly renewable materials. Since the total combinations (729) is considered a small number, an exhaustive search is applied to the data set to find the optimal value (Jain & Zongker, 1997). For this purpose, the total, DAM, cost and credits are calculated and the data is normalized by dividing every element by its column's maximum value. This is done so as to overcome a variation in the data range and transform the dataset into a more coherent and parochial range (0 to 1 in this case). The fitness function, as described in equation 5 is used to combine the three factors into a single number called the "fitness value". With limited activities, the exhaustive search can be used in this study. However, as in actual projects, this process is way more complicated when the number of activities increases, resulting in a large number of combinations (e.g. 320), which leads to combinatorial explosion (Tsang, 2005). Combinatorial explosion is an exponential increase in the size of combinations which prolongs the computational time significantly (Tsang, 2005). Hence the Genetic Algorithm is used to solve this problem as it reduces the computation time significantly (Jain & Zongker, 1997).

3.6 Genetic Algorithm (GAs)

GAs uses the theory of evolution to find the best possible outcome. The initial set of data is encoded into a chromosome (potential solution) which represents one of many potential solutions. The fitness of the solution is determined by evaluating the performance of chromosomes based on the objective function. The unfit chromosomes are eliminated by the process of survival of the fittest mechanism and offspring fitter than the parents are generated which replace the unfit members of the population (El-Rayes & Kandil, 2005; Mallawaarachchi, 2017; Whitley, 1994). This process continues until the criteria of a satisfactory solution is met which is called the "optimal or near optimal solution". The GAs evolution process can be divided into four major steps:

1. **Data Initialization**: Generation of initial set of solution (set of chromosomes)
2. **Fitness Function Evaluation**: Calculation of fitness values for each chromosome
3. **Mutation**: Randomly changing an element in a randomly chosen chromosome and removal of worst member (chromosome) of the population
4. **Crossover**: Selection of 2 best members (considered as parents), producing 2 child members, and removal of the worst member.

The flow process of the Genetic Algorithm described above is shown as in figure 5.

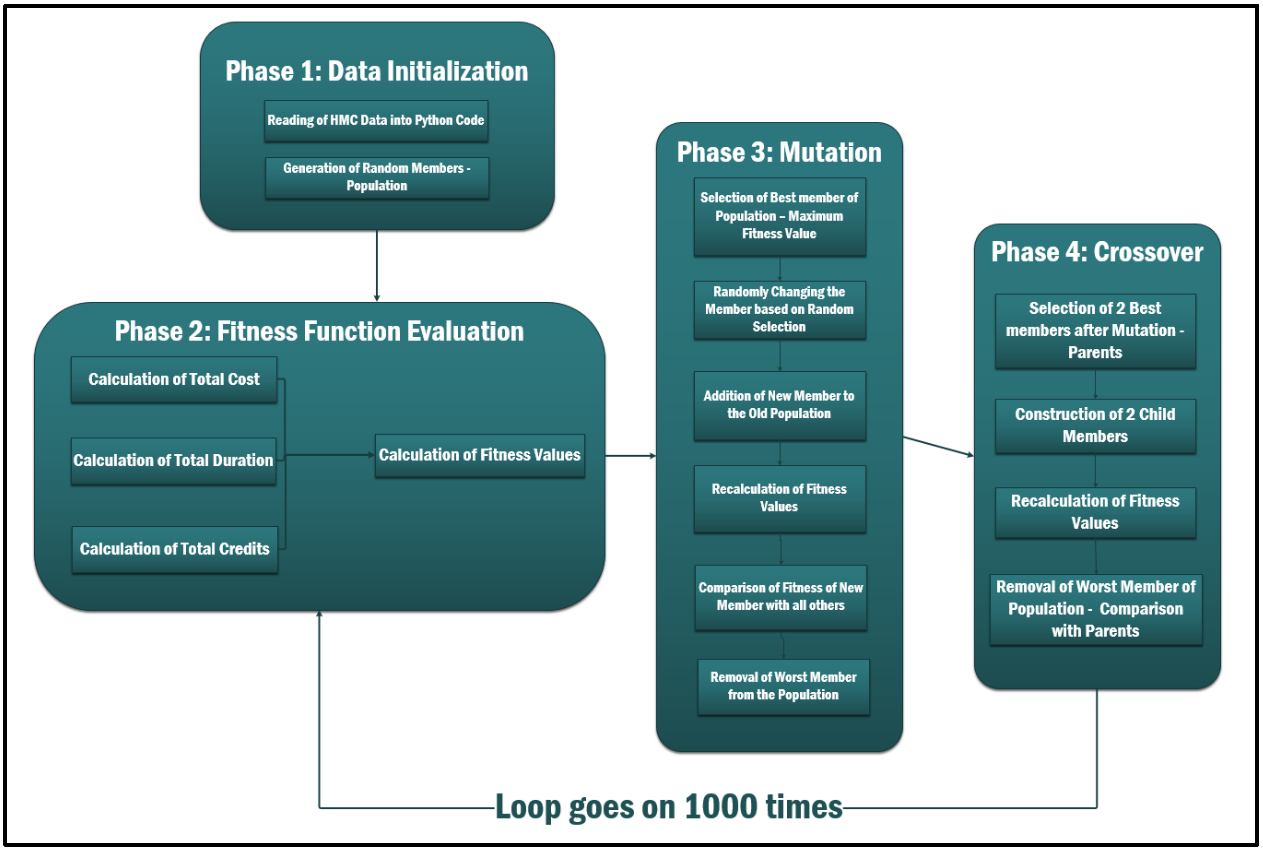

Figure 5: Genetic Algorithm

3.6.1 Phase 1 - Data Initialization

The first step in this algorithm is to initialize the data. This phase starts by importing the data into Python and defining 3 material options associated with each activity. This is essential because the data imported to Python is a cluster of numbers which have to be separated into 29 distinct activities, having 3 material options each. Hereupon, 10 random chromosomes are generated to make the population. A sample chromosome is shown below:

Table 1: Sample Chromosome

a0	a1	a2	….	a26	a27	a28
0	2	1	….	0	1	1

In table 1, each number represents the material option ranging from 0 to 2 (since there are a total of 3 options e.g. option 0, 1 and 2), for every single activity. A small number (10 in this case) of chromosomes is generated, as a “population”, which produce the offspring (child chromosomes) that will be evaluated using the fitness function in the following phase.

3.6.2 Phase 2 - Fitness Function Evaluation

Function for fitness calculation (Equation 5) is coded in Python which starts with the calculation of total MR credits for each combination and normalization of the matrix thereafter. To find the number of MR credits for each combination, the total sustainable criteria value for Recycle Content, Regional Materials and Rapidly Renewable Materials, are calculated and divided by the total cost of materials for the same combination. If the percentage is between 10% and 20%, then 1 credit is assigned, if its more than 20%, 2 credits are assigned, for each of Recycle Content and Regional Materials. 1 credit is assigned for Rapidly Renewable Materials if the renewable materials are more than 2.5% of total material cost. Considering all three sub categories for MR; a total of possible 5 credits could be achieved. To normalize the matrix, each option total (total DAM, total Material Cost and total credits) are divided by the respective column’s maximum value for each combination so that all numbers fall in the range of 0 to 1. Fitness for the 10 chromosomes is calculated using equation 5. The chromosome with the highest fitness is selected for usage in the mutation phase.

3.6.3 Phase 3 - Mutation

The selected chromosome is randomly mutated and the new chromosome is added to the old population. A sample mutation is shown as in table 2:

Table 2: Mutation of Chromosome

Original Chromosome	a0	a1	a2	….	a26	a27	a28
	0	2	1	….	0	1	1
Mutated Chromosome	a0	a1	a2	….	a26	a27	a28
	0	0	1	….	0	1	1

Table 2 shows a sample chromosome (The one with the highest fitness from the evaluation process in phase 2), which gets randomly mutated to form the mutated chromosome (mutated numbers are highlighted) assuming the numbers in between remained the same. It should be noted that the mutated chromosome is not overridden, but a clone of the original chromosome (with highest fitness) is created which then gets mutated. The fitness values are recalculated for the new population using equation 5. All the fitness values are compared to remove the worst chromosome of the population (with the lowest fitness value) before proceeding to the crossover phase

3.6.4 Phase 4 - Crossover

The Fitness is recalculated for the new population (after removal of the worst chromosome) and the two best chromosomes are selected (top two chromosomes) and crossed over to create two child chromosomes. A sample crossover has been shown below:

Table 3: Crossover of Parent Chromosomes

Parent 1	a0	a1	a2	….	a26	a27	a28
	0	0	1	….	2	1	0
Parent 2	a0	a1	a2	….	a26	a27	a28
	2	2	0	….	1	2	1
Child 1	a0	a1	a2	….	a26	a27	a28
	0	0	0	….	1	2	1
Child 2	a0	a1	a2	….	a26	a27	a28
	2	2	1	….	2	1	0

A random point of crossover is chosen from the first parent and the same point of crossover is used for the second parent. In table 3, the point of crossover is after a1 in the parents, where child 1 is created by combining the first half (before the point crossover) and the second half (after the point of crossover) of the second parent, and child 2 is created by combining the first half of the second parent (before the point of crossover) and the first half of the first parent (after the point of crossover). The two child chromosomes are added to the old population and the fitness values are calculated considering the new population. The fitness of child chromosomes is compared with the parent chromosomes and the two lowest fitness chromosomes out of the 4 members, are removed from the population.

Phase 2, 3 and 4 are reiterated 1000 times and the chromosome with the highest fitness value will be the resultant near optimal solution. The more the number of runs on the code (Phases 2, 3 and 4), the more optimal the solution can be (Haupt, 2000). Consider an analogy of tossing a coin. Probability of getting a Heads or a Tails increases with the number of tosses (trials). Similarly, in GAs Optimization models, the more the number of runs for the code, the more optimal the solution can be. Another contributor to achieving a more optimal solution is the initial population selection in Phase 1 where the initial sample population was constructed using 10 randomly selected chromosomes. Following the same logic, it can be inferred that the optimality of a solution can increase by increasing the number of runs, increasing the sample size (number of chromosomes) of initial population, or increasing both.

3.7 Validation Case Study

The validation case studies are required to substantiate the optimization model built using Python. It requires input of a larger data set and uses enhanced GA optimization model to solve the tradeoff. The validation study Python code can be referenced in Appendix B – Code for Validation Study.

3.7.1 Case study data collection and analysis

The first validation research focused on a LEED certified building (according to LEED 2009) and relevant data is obtained from the Facilities Management Department of Colorado State University (CSU) and Ambient Energy, the LEED consultant on the project. The project under study is the CSU Health and Medical Center (HMC), situated at the intersection of Prospect and College, in Fort Collins, Colorado. The project was completed in summer 2017 and achieved LEED Gold certification. The collected data comprises of three major domains namely: Material Cost, Duration Associated with Materials (DAM) and Credits associated with MR section of LEED. The duration of all the activities in consideration was obtained from Adolfson Peterson (the general contractor on the project), in the form of a construction schedule. The cost and credits data were both obtained from Ambient Energy, the LEED consultants on the project, in the form of the MR LEED calculator format. It consisted of different types of sustainable materials used on the HMC project with corresponding total cost of materials, sustainable criteria value for each of recycled content and regional materials. The second validation study operated on the same set of LEED variables and input data, considering a fire station project; for the purpose of just reinforcing the reliability of the optimization model.

3.7.2 Workflow Construct

In this research study, the Materials and Resources category is considered as part of the LEED certification criteria. Activities which pertain to the process of acquiring the credits for Materials and Resources are taken into consideration. . Cost data and the sustainable criteria value for each of the materials used, is extracted from the LEED data. The collected data were cleaned and 2 additional material options are added to the set, resulting in 3 material options for each execution able activity. The additional material options were obtained by telephonic or email conversations with different suppliers in and around Fort Collins and for each project activity the 3 material options included the cost, time and credits. At this stage, the dataset is ready to run through the GA optimization model in order to obtain near optimal results within the different scenarios that will be introduced in chapter 4.

Chapter 4: Data Analysis and Results

In this chapter, the datasets for preliminary and validation case studies are presented and explained, followed by the optimization model results and its tradeoff solutions.

4.1 Preliminary Study

The preliminary study data set shown in table 4, describes a dummy data set of a six activity project with 3 material options for each activity. Each material option will have its associated Cost, DAM and sustainable criteria values.

Table 4: Preliminary Data Set

		DAM (Time)	Cost ($)	MR1 ($)	MR2 ($)	MR3 ($)
Activity 1	**Method 1**	6	50	35	20	50
	Method 2	8	45	40	0	25
	Method 3	3	30	0	15	0
Activity 2	**Method 1**	7	55	45	55	0
	Method 2	6	40	40	40	25
	Method 3	5	31	15	31	10
Activity 3	**Method 1**	10	65	0	10	13
	Method 2	11	60	55	60	50
	Method 3	11	55	48	55	15
Activity 4	**Method 1**	5	100	65	98	45
	Method 2	8	120	0	0	0
	Method 3	6	150	120	150	50
Activity 5	**Method 1**	5	30	10	30	0
	Method 2	6	28	20	28	0
	Method 3	10	20	20	20	0
Activity 6	**Method 1**	10	85	85	85	0
	Method 2	11	78	70	75	65
	Method 3	12	70	65	60	60

Activity 1 to Activity 6, denote the different project activities (column 1), and each activity can be performed using 3 possible material options (column 2). Each method uses a unique material with an associated DAM and cost (columns 3 and 4 respectively). The following columns (columns 4, 5 and 6) are all associated with the MR sustainability criteria for each activity. Column 5 is associated with the sustainable criteria value for recycle content, calculated as a percentage of weights of recycled content. Column 6 represents the sustainable criteria value associated with regional materials which is calculated based on the percentage of components of a material which are manufactured in less than 500 miles of the project site. Column 7 is the sustainable criteria value for the rapidly renewable materials, which is calculated as a percentage of rapidly renewable content in the material. Following the methodology mentioned in the preliminary study, the RIFs are chosen by the user. The optimization model test runs considered 3 scenarios where the cost and time are minimized and credits are maximized according to the RIFs for each factor per scenario. The RIFs provides a method to mimic the factors prioritization based on stakeholder's needs in different scenarios. In this preliminary study, the overall minimum total DAM, minimum total cost and maximum total credits for the dummy set of activities taken into account were 38, 306, and 5, respectively.

For the first scenario, the DAM is assumed to be the most important (highest priority) factor, with the RIFs for DAM, cost and credits being 9, 1 and 1 respectively. Using the formulated optimization model, the optimized solution results for these weights (RIFs) are:

$$
\begin{array}{lccccc}
Activity\ 1 : Method\ 3 = & 3 & 30 & 0 & 15 & 0 \\
Activity\ 2 : Method\ 3 = & 5 & 31 & 15 & 31 & 10 \\
Activity\ 3 : Method\ 1 = & 10 & 65 & 0 & 10 & 13 \\
Activity\ 4 : Method\ 1 = & 5 & 100 & 65 & 98 & 45 \\
Activity\ 5 : Method\ 1 = & 5 & 30 & 10 & 30 & 0 \\
Activity\ 6 : Method\ 1 = & 10 & 85 & 85 & 85 & 0
\end{array}
$$

These results implied that Method 3 should be used for Activity 1, Method 3 for Activity 2, Method 1 for Activity 3, Method 1 for Activity 4, Method 1 for Activity 5 and Method 1 for Activity 6. The total DAM associated with this combination is 38 which is the same as the minimum DAM of the dataset. The result is in accordance with the user specified weights (RIFs), 9 being the highest importance for DAM and 1 being the lowest for Cost and Credits.

For the second scenario, the RIFs are changed so that the Cost has the highest priority. The RIFs for DAM, Cost and Credits for this scenario are 1, 9 and 1 respectively. The optimized solution obtained after running the model on the preliminary dataset with said RIFs is:

$$
\begin{array}{lccccc}
Activity\ 1 : Method\ 3 = & 3 & 30 & 0 & 15 & 0 \\
Activity\ 2 : Method\ 3 = & 5 & 31 & 15 & 31 & 10 \\
Activity\ 3 : Method\ 3 = & 11 & 55 & 48 & 55 & 15 \\
Activity\ 4 : Method\ 1 = & 5 & 100 & 65 & 98 & 45 \\
Activity\ 5 : Method\ 3 = & 10 & 20 & 20 & 20 & 0 \\
Activity\ 6 : Method\ 3 = & 12 & 70 & 65 & 60 & 60
\end{array}
$$

The total cost obtained for this combination of materials is 306 which is the same as minimum total cost among all the combinations. This result is coherent with user specified weights, highest being for the cost.

The third scenario in consideration is when the credits have the highest priority. RIFs for this case are 1, 1 and 9, and the optimized solution results is:

$$
\begin{array}{lccccc}
Activity\ 1 : Method\ 3 = & 3 & 30 & 0 & 15 & 0 \\
Activity\ 2 : Method\ 3 = & 5 & 31 & 15 & 31 & 10 \\
Activity\ 3 : Method\ 3 = & 11 & 55 & 48 & 55 & 15 \\
Activity\ 4 : Method\ 1 = & 5 & 100 & 65 & 98 & 45 \\
Activity\ 5 : Method\ 1 = & 5 & 30 & 10 & 30 & 0 \\
Activity\ 6 : Method\ 1 = & 10 & 85 & 85 & 85 & 0
\end{array}
$$

5 credits are obtained for this combination, being in accordance with the total maximum credits that could be obtained (which is 5). This shows that the RIFs determine the optimal solution and a user could define them to provide the minimum DAM or cost and maximum credits.

Based on the preliminary results, the DAM and cost are minimized and credits are maximized based on the priority factors entered by the user, hence verifying the authenticity of the mathematical equations, constraints and fitness function. The Python code follows the exhaustive search for the preliminary study and the solutions obtained are the most optimal among all possible combinations. However, in the validation case study, the number of combinations rises exponentially as the number of activities in a "real project" increases and using exhaustive search on the data set needs more computational power and time. Therefore, the GA optimization model was introduced to tackle the problem of computational inefficiency.

4.2 Validation Case Study 1

The validation case study takes the previously identified HMC datasets as an input and runs the GA optimization model on the dataset while capturing user priority inputs in the form of RIFs to come up with optimal solutions. There are a total of 29 activities and 3 material options for each, making a total of 3^{29} combinations. This cannot be solved using exhaustive search due to higher computational power required to run and solve the optimization functions with a bigger dataset (Haupt, 2000). Therefore, the Genetic Algorithm was introduced in the optimization model based on the four aforementioned phases (initialization, fitness evaluation, Mutation and crossover). A sample table for the HMC data showing the first three and last three activities is shown in table 5 and the complete dataset can be found in Appendix C-HMC Case study Full Dataset. In table 5, Column 1 describes the activities as executed for the HMC project. For each activity, there are 3 unique material options introduced in the 2nd column, each of which have an associated DAM (Column 4), material cost (Column 5), and sustainable criteria values (Column 6, 7 and 8). This serves as the data set for the validation study which was imported into Python 3.5 before running the GA optimization model.

Table 5: HMC Data Set

Activity Name	Material	DAM	Cost	MR1	MR2	MR3
Concrete	Material 1	30	154900	$0.00	$125,469.00	$0.00
	Material 2	28	376533	$16,907.00	$376,533.00	$0.00
	Material 3	27	337036	$15,167.00	$337,036.00	$0.00
Concrete - Cast in Place	Material 1	25	218656	$0.00	$218,656.00	$0.00
	Material 2	20	564799	$25,360.00	$564,799.00	$0.00
	Material 3	23	505554	$22,750.00	$505,554.00	$0.00
Rebar - Cast in Place	Material 1	20	238257	$218,006.00	$238,257.00	$0.00
	Material 2	20	795710	$698,633.00	$795,710.00	$0.00
	Material 3	20	901804	$844,089.00	$901,804.00	$0.00
Flooring-Resilient	Material 1	26	30406	$5,170.00	$0.00	$0.00
	Material 2	25	151868	$25,818.00	$151,868.00	$0.00
	Material 3	26	151414	$25,741.00	$151,414.00	$0.00
Flooring-Tile	Material 1	16	68414	$11,973.00	$0.00	$0.00
	Material 2	14	86242	$15,093.00	$86,242.00	$0.00
	Material 3	12	86304	$15,104.00	$86,304.00	$0.00
Flooring-Rubber Base	Material 1	21	20608	$1,443.00	$0.00	$0.00
	Material 2	19	20608	$1,443.00	$20,608.00	$0.00
	Material 3	21	20608	$1,443.00	$20,608.00	$0.00

The total DAM, Cost and Credits for the combination used originally on HMC project are 794 days, $ 5,818,463.00 and 4 credits respectively. After running the GA optimization model for 1000 times through different scenarios, the results were obtained in the form of a set of values that represent the optimal solution for each of the four scenarios shown below.

For the first scenario, the DAM is assumed to be the most important (highest priority) factor, with the RIFs for DAM, cost and credits being 9, 1 and 1 respectively. The optimized solution for these weights is as shown in table 6:

Table 6: Scenario 1 (9, 1, 1)

Activity Name	Method	DAM	Cost ($)	MR1 ($)	MR2 ($)	MR3 ($)
Activity 1	Method 3	27	337036	15167	337036	0
Activity 2	Method 2	20	564799	25360	564799	0
Activity 3	Method 1	20	238257	218006	238257	0
Activity 4	Method 2	22	200000	183000	200000	0
Activity 5	Method 2	4	250000	75000	250000	12500
Activity 6	Method 3	9	42843	1778	0	86
Activity 7	Method 2	37	170000	52700	170000	8500
Activity 8	Method 2	40	13722	0	0	0
Activity 9	Method 2	40	80997	6075	80997	0
Activity 10	Method 3	1	303	271	303	0
Activity 11	Method 2	4	7961	598	7961	0
Activity 12	Method 2	25	54850	1591	54850	3182
Activity 13	Method 2	40	25000	9375	25000	0
Activity 14	Method 2	36	127253	37540	127253	0
Activity 15	Method 2	1	1333	708	0	0
Activity 16	Method 2	22	12000	4500	12000	0
Activity 17	Method 2	3	4000	1260	4000	80
Activity 18	Method 3	46	130000	39000	130000	0
Activity 19	Method 3	70	273579	1751284	31346	0
Activity 20	Method 2	50	100000	55000	0	5000
Activity 21	Method 2	28	151620	593085	0	0
Activity 22	Method 2	7	65000	40300	65000	3250
Activity 23	Method 3	8	0	0	0	0
Activity 24	Method 3	58	75000	15000	0	750
Activity 25	Method 3	14	64508	5561	64508	0
Activity 26	Method 2	35	140000	52500	140000	0
Activity 27	Method 1	26	30406	5170	0	0
Activity 28	Method 3	12	86304	15104	86304	0
Activity 29	Method 2	19	20608	1443	20608	0

Total DAM for this combination is 764 working days and total cost associated is $ 6,281,101, and the total achievable credits is 4. DAM is seen to be lesser than the DAM for the combination used on HMC (which was 794 days).

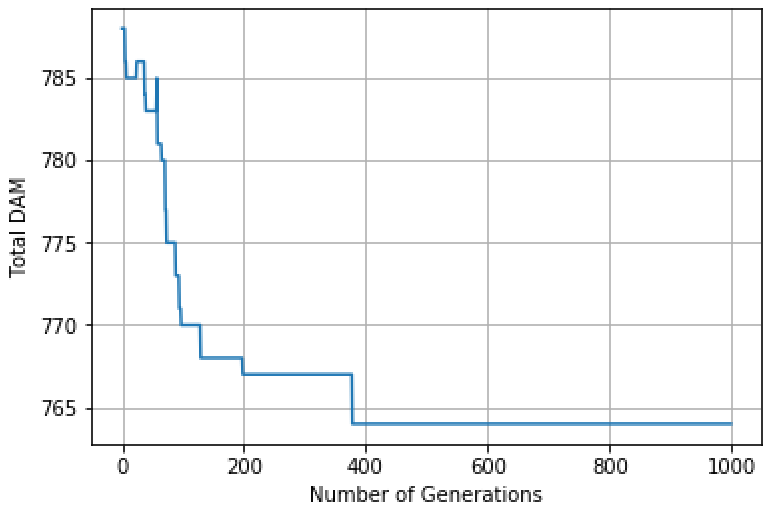

Figure 6: Trend in Total DAM with increase in number of generations

For the second scenario, the cost is assumed to be the most important (highest priority) factor, with the RIFs for DAM, cost and credits being 1, 9 and 1 respectively. The optimized solution for these weights are shown in table 7:

Table 7: Scenario 2 (1, 9, 1)

Activity Name	Method	DAM	Cost ($)	MR1 ($)	MR2 ($)	MR3 ($)
Activity 1	Method 1	30	154900	0	125469	0
Activity 2	Method 1	25	218656	0	218656	0
Activity 3	Method 1	20	238257	218006	238257	0
Activity 4	Method 3	24	198000	181170	198000	0
Activity 5	Method 1	5	196600	70776	68810	0
Activity 6	Method 1	13	23684	0	22263	0
Activity 7	Method 2	37	170000	52700	170000	8500
Activity 8	Method 2	40	13722	0	0	0
Activity 9	Method 2	40	80997	6075	80997	0
Activity 10	Method 3	1	303	271	303	0
Activity 11	Method 2	4	7961	598	7961	0
Activity 12	Method 2	25	54850	1591	54850	3182
Activity 13	Method 1	42	20548	6165	0	0
Activity 14	Method 1	38	32399	26568	0	0
Activity 15	Method 2	1	1333	708	0	0
Activity 16	Method 1	23	10790	1457	0	0
Activity 17	Method 2	3	4000	1260	4000	80
Activity 18	Method 1	50	117086	35126	117086	0

Activity 19	Method 3	70	2273579	1751284	31346	0
Activity 20	Method 1	55	94069	47035	0	0
Activity 21	Method 1	30	1103620	568365	0	0
Activity 22	Method 2	7	65000	40300	65000	3250
Activity 23	Method 3	8	0	0	0	0
Activity 24	Method 2	60	71511	14303	0	0
Activity 25	Method 1	17	14599	6570	0	0
Activity 26	Method 2	35	140000	52500	140000	0
Activity 27	Method 1	26	30406	5170	0	0
Activity 28	Method 1	16	68414	11973	0	0
Activity 29	Method 2	19	20608	1443	20608	0

The total DAM obtained for this combination is 804 working days, cost being $ 5,439,614 and 4 achievable credits. The cost is seen to be less than the cost for HMC combination (which was $ 5,818,463), validating that the cost did get minimized by setting the RIFs in favor of cost.

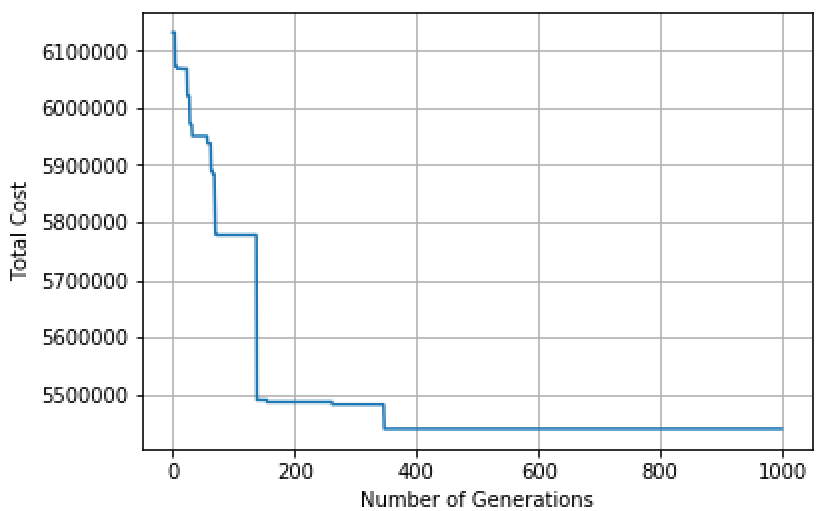

Figure 7: Trend of Total Cost with increase in number of generations

For the third scenario, the credits are assumed to be the most important (highest priority) factor, with the RIFs for DAM, cost and credits being 1, 1 and 9 respectively. The optimized solution for these weights are shown in table 8:

Table 8: Scenario 3 (1, 1, 9)

Activity Name	Method	DAM	Cost ($)	MR1 ($)	MR2 ($)	MR3 ($)
Activity 1	Method 1	30	154900	0	125469	0
Activity 2	Method 1	25	218656	0	218656	0
Activity 3	Method 1	20	238257	218006	238257	0
Activity 4	Method 2	22	200000	183000	200000	0
Activity 5	Method 1	5	196600	70776	68810	0
Activity 6	Method 3	9	42843	1778	0	86
Activity 7	Method 2	37	170000	52700	170000	8500
Activity 8	Method 2	40	13722	0	0	0
Activity 9	Method 2	40	80997	6075	80997	0
Activity 10	Method 3	1	303	271	303	0
Activity 11	Method 2	4	7961	598	7961	0
Activity 12	Method 2	25	54850	1591	54850	3182
Activity 13	Method 2	40	25000	9375	25000	0
Activity 14	Method 1	38	32399	26568	0	0
Activity 15	Method 2	1	1333	708	0	0
Activity 16	Method 2	22	12000	4500	12000	0
Activity 17	Method 2	3	4000	1260	4000	80
Activity 18	Method 3	46	130000	39000	130000	0
Activity 19	Method 3	70	2273579	1751284	31346	0
Activity 20	Method 2	50	100000	55000	0	5000
Activity 21	Method 1	30	1103620	568365	0	0
Activity 22	Method 2	7	65000	40300	65000	3250
Activity 23	Method 3	8	0	0	0	0
Activity 24	Method 3	58	75000	15000	0	750
Activity 25	Method 1	17	14599	6570	0	0
Activity 26	Method 2	35	140000	52500	140000	0
Activity 27	Method 1	26	30406	5170	0	0
Activity 28	Method 3	12	86304	15104	86304	0
Activity 29	Method 2	19	20608	1443	20608	0

Total DAM for this combination is 804 working days, total cost is $ 5,439,614 and total maximum achievable credits is 4 which is in accordance with the baseline data of HMC project, which achieved 4 credits as well.

Forth scenario is a mixed priorities scenario, with the RIFs for DAM, cost and credits being 4, 2 and 9 respectively. The optimized solution for these weights are shown in table 9:

Table 9: Scenario 4 (4, 2, 9)

Activity Name	Method	DAM	Cost ($)	MR1 ($)	MR2 ($)	MR3 ($)
Activity 1	Method 1	30	154900	0	125469	0
Activity 2	Method 1	25	218656	0	218656	0
Activity 3	Method 1	20	238257	218006	238257	0
Activity 4	Method 2	22	200000	183000	200000	0
Activity 5	Method 1	5	196600	70776	68810	0
Activity 6	Method 3	9	42843	1778	0	86
Activity 7	Method 2	37	170000	52700	170000	8500
Activity 8	Method 2	40	13722	0	0	0
Activity 9	Method 2	40	80997	6075	80997	0
Activity 10	Method 3	1	303	271	303	0
Activity 11	Method 2	4	7961	598	7961	0
Activity 12	Method 2	25	54850	1591	54850	3182
Activity 13	Method 2	40	25000	9375	25000	0
Activity 14	Method 1	38	32399	26568	0	0
Activity 15	Method 2	1	1333	708	0	0
Activity 16	Method 2	22	12000	4500	12000	0
Activity 17	Method 2	3	4000	1260	4000	80
Activity 18	Method 3	46	130000	39000	130000	0
Activity 19	Method 3	70	2273579	1751284	31346	0
Activity 20	Method 2	50	100000	55000	0	5000
Activity 21	Method 1	30	1103620	568365	0	0
Activity 22	Method 2	7	65000	40300	65000	3250
Activity 23	Method 3	8	0	0	0	0
Activity 24	Method 3	58	75000	15000	0	750
Activity 25	Method 1	17	14599	6570	0	0
Activity 26	Method 2	35	140000	52500	140000	0
Activity 27	Method 1	26	30406	5170	0	0
Activity 28	Method 3	12	86304	15104	86304	0
Activity 29	Method 2	19	20608	1443	20608	0

Total DAM obtained for this combination is 780 working days, total cost being $ 5,506,659 and total achievable 4 credits. Both the total DAM and cost are less than the baseline combination for HMC, validating the model yet again.

It can be seen that the project factors are optimized very efficiently based on RIFs' definition, providing a time and cost within or under the project. This study also validates the GA optimization model in providing the optimized set of solution. Next section discusses the limitations in this research, future study and conclusion.

It can be seen that the project factors are optimized very efficiently based on RIFs' definition, providing a time and cost within or under the project. This study also validates the GA optimization model in providing the optimized set of solution.

4.2.1 Dependence of optimality on Population size and Number of runs

The optimality of the solutions depends on the initial population size and the number of runs for the GA. Several scenarios were executed to validate this dependence by keeping the relative importance factors fixed (DAM having highest importance in all scenarios) while manipulating the number of runs or the population size. The results are summarized in table 10 where in one case, the population size was kept as 10 and the number of runs was increased from 30 to 1000 in scenario number (Sc.no.) 1 and 2.

Table 10: Dependence of Optimality of population size and runs

S.no.	Population Size	No. of Runs	Total DAM (days)	Computation Time (seconds)
1	10	30	736	0.55732892
2	10	1000	724	5.416013707
3	15	30	748	0.600213413
4	25	30	735	0.760430409

It can be seen that the total DAM decreased from 736 days to 724 days as the number of runs increased from 30 to 1000 (scenario 1 and 2), respectively. In another case, the population size was increased while keeping the number of runs constant. It can be seen that the total DAM decreased from 748 days to 735 days as the initial population size was increased from 15 to 25 (scenario 3 and 4), respectively. The computational time required to run every scenario has been tabulated in table 10.

4.3 Validation Case Study 2

Another case study was taken into account to reinforce the validity of the optimization model. For the second validation case study, a fire station project was chosen and GA optimization model was applied to find the optimal solutions. The dataset has 15 different activities and 3 material options associated with each activity, making a total of 3^{15} combinations.

Table 11: Fire Station Data Set

Activity		DAM (days)	Cost	MR1	MR2	MR3
Concrete - Cast in Place	Material 1	10	$93,008.00	$0.00	$93,008.00	$0.00
	Material 2	8	$100,000.00	$14,000.00	$100,000.00	$5,800.00
	Material 3	7	$56,326.00	$14,082.00	$56,326.00	$4,281.00
Rebar - Cast in Place	Material 1	3	$7,368.00	$6,742.00	$7,368.00	$0.00
	Material 2	3	$10,000.00	$9,700.00	$10,000.00	$0.00
	Material 3	3	$8,265.00	$10,125.00	$8,265.00	$521.00
Pre-Cast	Material 1	4	$134,422.00	$126,357.00	$86,030.00	$0.00
	Material 2	4	$120,000.00	$112,800.00	$102,000.00	$0.00
	Material 3	5	$150,326.00	$139,052.00	$0.00	$6,765.00

Therefore, the Genetic Algorithm was introduced in the optimization model based on the four aforementioned phases (initialization, fitness evaluation, Mutation and crossover). A sample table for the fire station project data showing some activities is shown in Table *11,* and the complete dataset can be found in Appendix D – Fire Station Full Dataset. In table 11, Column 1 describes the activities as executed for the fire station project. For each activity, there are 3 unique material options introduced in the 2nd column, each of which have an associated DAM (Column 4), material cost (Column 5), and sustainable criteria values (Column 6, 7 and 8). This serves as the data set for the validation study which was imported into Python 3.5 before running the GA optimization model.

The total DAM, Cost and Credits for the combination used originally on fire station project are 95 days, $ 580,564 and 4 credits respectively. After running the GA optimization model for 1000 times through different scenarios, the results were obtained in the form of a set of values that represent the optimal solution for each of the four scenarios shown below.

For the first scenario, the DAM is assumed to be the most important (highest priority) factor, with the RIFs for DAM, cost and credits being 9, 1 and 1 respectively. The optimized solution for these weights is as shown in table 12:

Table 12: Scenario 1 (9,1,1)

Activity	DAM (days)	Cost	MR1	MR2	MR3
Activity 1	7	$56,326.00	$14,082.00	$56,326.00	$4,281.00
Activity 2	3	$7,368.00	$6,742.00	$7,368.00	$0.00
Activity 3	4	$120,000.00	$112,800.00	$102,000.00	$0.00
Activity 4	10	$16,326.00	$4,898.00	$0.00	$2,580.00
Activity 5	6	$11,236.00	$9,551.00	$0.00	$292.00
Activity 6	11	$6,258.00	$1,877.00	$0.00	$812.00
Activity 7	10	$20,000.00	$27,500.00	$20,000.00	$1,200.00
Activity 8	5	$85,625.00	$65,931.00	$72,781.00	$12,844.00
Activity 9	5	$16,326.00	$17,550.00	$16,326.00	$0.00
Activity 10	3	$13,910.00	$7,998.00	$13,910.00	$0.00
Activity 11	8	$125,653.00	$30,157.00	$0.00	$0.00
Activity 12	3	$87,984.00	$27,715.00	$0.00	$0.00
Activity 13	4	$4,377.00	$744.00	$0.00	$0.00
Activity 14	2	$4,562.00	$912.00	$2,965.00	$274.00
Activity 15	6	$2,456.00	$0.00	$0.00	$246.00

Total DAM for this combination is 87 working days and total cost associated is $ 578,407, and the total achievable credits is 5. DAM is seen to be lesser than the DAM for the combination used on HMC (which was 95 days).

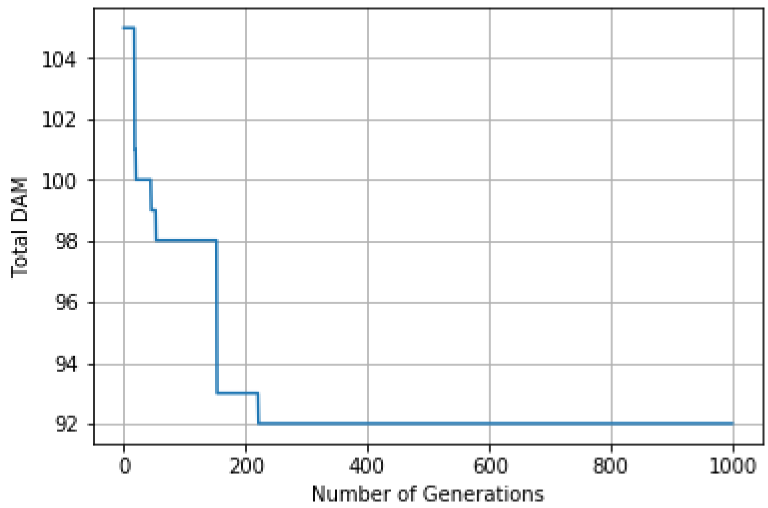

Figure 8: Trend in total DAM with increase in Number of Generations

For the second scenario, the cost is assumed to be the most important (highest priority) factor, with the RIFs for DAM, cost and credits being 1, 9 and 1 respectively. The optimized solution for these weights are shown in table 13.

Table 13: Scenario 2 (1,9,1)

Activity	DAM (days)	Cost	MR1	MR2	MR3
Activity 1	7	$56,326.00	$14,082.00	$56,326.00	$4,281.00
Activity 2	3	$7,368.00	$6,742.00	$7,368.00	$0.00
Activity 3	4	$120,000.00	$112,800.00	$102,000.00	$0.00
Activity 4	10	$16,326.00	$4,898.00	$0.00	$2,580.00
Activity 5	6	$11,236.00	$9,551.00	$0.00	$292.00
Activity 6	15	$1,000.00	$460.00	$150.00	$0.00
Activity 7	10	$20,000.00	$27,500.00	$20,000.00	$1,200.00
Activity 8	5	$85,625.00	$65,931.00	$72,781.00	$12,844.00
Activity 9	5	$16,326.00	$17,550.00	$16,326.00	$0.00

Activity 10	4	$10,259.00	$6,361.00	$0.00	$0.00
Activity 11	8	$125,653.00	$30,157.00	$0.00	$0.00
Activity 12	4	$75,321.00	$7,532.00	$48,959.00	$2,636.00
Activity 13	4	$4,377.00	$744.00	$0.00	$0.00
Activity 14	2	$4,562.00	$912.00	$2,965.00	$274.00
Activity 15	6	$2,456.00	$0.00	$0.00	$246.00

Total DAM for this combination is 93 working days and total cost associated is $ 556,835, and the total achievable credits is 5. DAM is seen to be lesser than the DAM for the combination used on HMC (which was 95 days). The cost is seen to be less than the cost for the fire station dataset combination (which was $ 580,564), validating that the cost did get minimized by setting the RIFs in favor of cost.

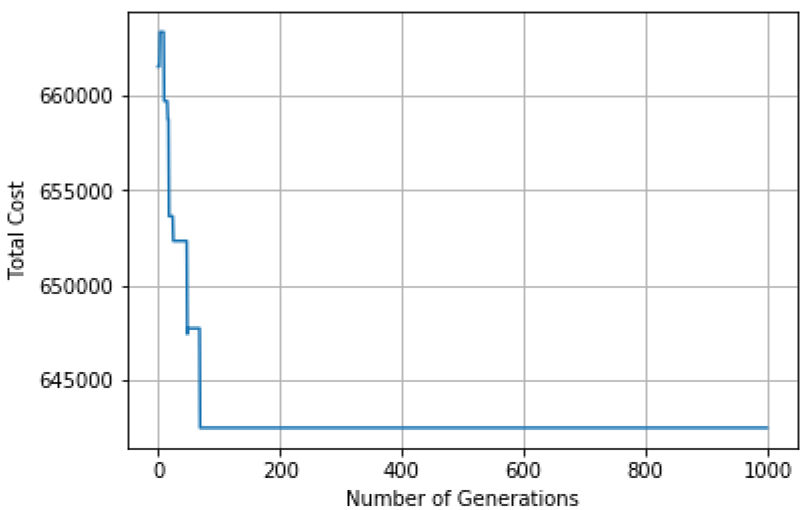

Figure 9: Trend in total cost with increase in Number of Generations

Forth scenario is a mixed priorities scenario, with the RIFs for DAM, cost and credits being 4, 2 and 9 respectively. The optimized solution for these weights are shown in

Table 14: Scenario 3 (4,2,9)

DAM (days)	Cost	MR1	MR2	MR3
7	$56,326.00	$14,082.00	$56,326.00	$4,281.00
3	$7,368.00	$6,742.00	$7,368.00	$0.00
4	$120,000.00	$112,800.00	$102,000.00	$0.00
10	$16,326.00	$4,898.00	$0.00	$2,580.00
6	$11,236.00	$9,551.00	$0.00	$292.00
11	$6,258.00	$1,877.00	$0.00	$812.00
10	$20,000.00	$27,500.00	$20,000.00	$1,200.00
5	$85,625.00	$65,931.00	$72,781.00	$12,844.00
5	$16,326.00	$17,550.00	$16,326.00	$0.00
3	$13,910.00	$7,998.00	$13,910.00	$0.00
8	$125,653.00	$30,157.00	$0.00	$0.00
3	$87,984.00	$27,715.00	$0.00	$0.00
4	$4,377.00	$744.00	$0.00	$0.00
2	$4,562.00	$912.00	$2,965.00	$274.00
6	$2,456.00	$0.00	$0.00	$246.00

Total DAM obtained for this combination is 87 working days, total cost being $ 578,407 and total achievable 5 credits. Both the total DAM and cost are less than the baseline combination for HMC, validating the model yet again.

It can be seen that the project factors are optimized very efficiently based on RIFs' definition, providing a time and cost within or under the project. This study also validates the GA optimization model in providing the optimized set of solution. Next section discusses the limitations in this research, future study and conclusion.

Chapter 5: Findings, Discussion and Conclusion

5.1 Research Summary

This research aimed to answer the research questions posed to solve the identified tradeoff between the cost, time and sustainability which was represented in the MR LEED category. In answering the research questions, the optimization technique was found to be the most suited to solve the tradeoff problem. Among the many types of optimization techniques, the multi-objective optimization was determined to be the befitting optimization type along with using the GA technique to solve the complexity of the problem and overcome the computational difficulties. Based on these choices, a mathematical model, represented in the multi-objective function, was formulated along with several problem constraints. The model's mathematical capability was tested using a preliminary study before adding the GA technique and another case study was analyzed using the GA optimization model for model validation and optimal solving capability demonstration.

5.2 Findings and Discussion

The preliminary study was used to run a sample data set on the optimization model created in Python, following the exhaustive search algorithm. It presents the most optimal solution based on user entered RIFs for time, cost and credits. The model is seen to be coherent with the attainable minimum cost and time, and maximum credits among all possible combinations. Another "real project" case study was used as a validation study after applying the genetic algorithm, while also considering the user input as RIFs to test the ability of solving for a tradeoff optimal/near-optimal solutions. It can be seen from the results that the optimal solution depends on three main factors:

1. The initial size of the population (containing a set of chromosomes)

2. The Relative Importance Factors (RIFs) entered by the user
3. Number of runs for the genetic algorithm code

In this optimization model, the user defines the RIFs for time, cost and credits, which give a different optimal solution based on the user input. For example, cost would be given the priority to be minimized if the RIF for cost is the highest (meaning budget has the highest priority for the user). The number of runs for the genetic algorithm code determines the level of optimality of solution obtained, where a large number of runs mean that the initial population goes through mutation and crossover many more times, which increases the probability of finding an optimal solution. Recalling table 10, it is evident that as the number of runs was increased, the solution became more optimal (lower total DAM in that case). Similarly, when the model ran varying population sizes, it was found that the bigger the size of initial population, the better the optimal solution can be. This is due to the more number of combinations considered in a bigger population, hence increasing the probability of finding the optimal/near optimal solution. To strengthen the reliability of the optimization model, it was ran again using a dataset from a fire station project and it was seen to work in concordance with the priority factors set by the user.

These factors show that in order to reach the most optimal solution or to increase the level of optimality, it is necessary to compute a wide range of combinations (either having a large initial population or having more runs in genetic algorithm) which further justifies the use of the GAs due to its computational efficiency. It should be noted from table 10 that the effect of increase of number of runs is more than increasing population size, as more number of chromosomes could be introduced in the population. Computational time increases with increase in population size because the GA would run the whole population size every time the fitness values need to be calculated (Haupt, 2000). It can be seen from table 10 that the computational time increases with the number of runs and with the increased population size. The increase in computational time is greater, when numbers of runs is increased as compared to the population size, however, having a tradeoff with the optimality of solution. Hence the user needs to decide the level of optimality required and its tradeoff with the computational time required. This time would increase exponentially as the size of dataset increases. It is expected that the solution would be the most optimal if the GA is left to run for a sufficient time (large number of runs).

5.3 Conclusion

The optimization model created in this research uses genetic algorithm, which is one of the most dynamic and user friendly evolutionary coding techniques. The model works efficiently and run 1000 times with changing RIFs to yield optimal solutions which can minimize a project's cost and DAM, while maximizing the earned credits. This optimization model is beneficial to different stakeholders in the construction industry. It can reduce the workload of LEED consultants exponentially, by providing them with material options to use based on the importance factors provided by the owners. Similarly, Design-Builders can use it to optimize the owner's budget while attaining the maximum credits for the LEED certification and reducing the risk of their schedules.

In many cases, the owners (mostly state and federal facility owners, e.g. Educational facilities) have to meet certain minimal requirements for building certification and this model can be a time and cost efficient method of achieving the best possible material combinations for the cheapest price and highest number of attainable credits. The optimization model created to fulfill the purpose of this research is very dynamic and works with any datasets in the required format (DAM, cost, sustainable criteria values for MR1, MR2 and MR3 in order from left to right) as shown in both, the preliminary and the validation case studies where it worked in different project sizes. The optimization model developed in this research has been seen to be highly successful in the preliminary study, which created a premise for the validation study using HMC data. The success from the validation study shows that the model not only works at the theoretical level, but also at a practical level and has the potential of getting embedded in a software package for industry use. Coding is highly dynamic and user friendly to new data sets and inexperienced users, respectively. The optimization model takes into account user defined priorities which can provide them with easy and efficient solution to these kinds of tradeoffs.

5.4 Limitations and Future Study

This research considers LEED version 2009 for credits' calculation, even though the latest version for LEED is V4. The reason for using LEED 2009 in this research study was that most completed projects have been certified using LEED 2009 and certification for projects in version V4 is still in progress. Another limitation of this study is that only the material and resources category of LEED has been considered due to the time constraints and data availability within the study. Finally, the DAM, which is the duration associated with materials is added directly, considering all activities on the critical path and the study didn't utilize resource utilization pools to determine the critical activities. However, based on the previous literature about the effects of reducing the duration of both critical and non-critical activities, the value was still observed in the time reduction in, as a positive effect on the project by either minimizing the duration of the project or minimizing the risk associated with activity execution time.

As part of future study, the whole LEED system or any of the other certification systems could be chosen for optimization. Also, as the data pool for LEED V4 increases, the projects certified in accordance with the new version, can be used as the validation data set. Finally, a resource utilization plan can be used in determining the criticality of activities which can allow for optimizing the targeted project critical path and not just the duration of a combination of activities.

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Appendix A – Code for Preliminary Study

```
import numpy as np
from random import randint
from math import factorial

import pandas as pd
df = pd.read_excel('Preliminary Data for thesis defense.xlsx')
A = df.as_matrix()
A

A1 = np.array(A[0:3,:])
A1

A2 = np.array(A[3:6,:])
A2

A3 = np.array(A[6:9,:])
A3

A4 = np.array(A[9:12,:])
A4

A5 = np.array(A[12:15,:])
A5

A6 = np.array(A[15:18,:])
A6
```

```
combo_i = []
for i1 in [0,1,2]:
    for i2 in [0,1,2]:
        for i3 in [0,1,2]:
            for i4 in [0,1,2]:
                for i5 in [0,1,2]:
                    for i6 in [0,1,2]:
                        combo_i.append(np.array([i1,i2,i3,i4,i5,i6]))


SOC = np.asarray(combo_i)
print SOC


len(combo_i)


sol =
np.array([[A1[SOC[0,0]],A2[SOC[0,1]],A3[SOC[0,2]],A4[SOC[0,3]],A5[SOC[0,4]],A6[SOC[0,
5]]]])
sol


Cost_Sum_j = []
Time_Sum_j = []
Total_Cr_j =[]
for j in range(729):
    Solution_j =
np.array([A1[SOC[j,0]],A2[SOC[j,1]],A3[SOC[j,2]],A4[SOC[j,3]],A5[SOC[j,4]],A6[SOC[j,5]]]
)
    Time_Sum_j.append(np.sum(Solution_j[:,0]))
    Cost_Sum_j.append(np.sum(Solution_j[:,1]))
    Cost_Sum = np.sum(Solution_j[:,2])
    MR1_Sum = np.sum(Solution_j[:,2])
```

```
MR2_Sum = np.sum(Solution_j[:,3])
MR3_Sum = np.sum(Solution_j[:,4])

Perc_MR1 = (float(MR1_Sum)/float(Cost_Sum))*100
Perc_MR2 = (float(MR2_Sum)/float(Cost_Sum))*100
Perc_MR3 = (float(MR3_Sum)/float(Cost_Sum))*100

if ((Perc_MR1>=10) & (Perc_MR1<20)):
    Cr1 = 1
elif Perc_MR1>=20:
    Cr1 = 2
else:
    Cr1 = 0



if ((Perc_MR2>=10) & (Perc_MR2<20)):
    Cr2 = 1
elif Perc_MR2>=20:
    Cr2 = 2
else:
    Cr2 = 0

if (Perc_MR3>=2.5):
    Cr3 = 1
else:
    Cr3 = 0

Total_Cr_j.append(Cr1+Cr2+Cr3)
```

```
CostSum = np.asarray(Cost_Sum_j)
print CostSum

TimeSum = np.asarray(Time_Sum_j)
print TimeSum

CreditSum = np.asarray(Total_Cr_j)
print CreditSum

np.size(CostSum)

TimeSum.size

Mat = np.vstack(((CostSum,TimeSum),CreditSum))
Mat

Final_Mat = np.transpose(Mat.astype(float))
Final_Mat

p = np.max(CostSum)
p

q = np.max(TimeSum)
q

r = np.max(CreditSum)
r
```

```
Norm_Cost = Final_Mat[:,0]/float(p)
Norm_Cost

np.size(Norm_Cost)

Norm_Time = Final_Mat[:,1]/float(q)
Norm_Time

Norm_Credit = Final_Mat[:,2]/float(r)
Norm_Credit

Norm = np.vstack(((Norm_Cost,Norm_Time),Norm_Credit))
Norm

Norm[0,0]

Normalized_Mat = np.transpose(Norm)
Normalized_Mat

Wc = input('Enter the importance factor for time:')
Wt = input('Enter the importance factor for cost:')
Wcr = input('Enter the importance factor for credits:')

Fitness_k = []
for k in range(729):
    Fitness_k.append(-Normalized_Mat[k,0]*(float(Wt)/(Wt+Wc+Wcr)) -
Normalized_Mat[k,1]*(float(Wc)/(Wt+Wc+Wcr)) +
Normalized_Mat[k,2]*(float(Wcr)/(Wt+Wc+Wcr)))
```

```
Fitval = np.asarray(Fitness_k)
print Fitval

np.size(Fitval)

Fitval[1]

Fitness_Values = np.transpose(Fitval)
Fitness_Values

Max_Fit = np.max(Fitness_Values)
Max_Fit

Min_Fit = np.min(Fitness_Values)
Min_Fit

m = np.argmax(Fitness_Values)
m

n = np.argmin(Fitness_Values)
n

SOC[m,:]
array([2, 2, 2, 0, 0, 0])

Optimal_Sol = []
Optimal_Sol =
np.array([[A1[SOC[m,0],:],A2[SOC[m,1],:],A3[SOC[m,2],:],A4[SOC[m,3],:],A5[SOC[m,4],:],
A6[SOC[m,5],:]]])
```

Optimal_Sol

np.min(TimeSum)

np.min(CostSum)

np.sum(Optimal_Sol[:,0])

CreditSum[m]

TimeSum[m]

CostSum[m]

CreditSum[m]

Appendix B – Code for Validation Study

```
import numpy as np

from random import randint


import pandas as pd

df = pd.read_excel('Validation data set_2.xlsx')

A = df.as_matrix()

A


import pdb

%pdb off

Automatic pdb calling has been turned OFF


np.shape(A)


A1 = np.array(A[0:3,:])

A1


A2 = np.array(A[3:6,:])

A2


A3 = np.array(A[6:9,:])

A3


A4 = np.array(A[9:12,:])

A4


A5 = np.array(A[12:15,:])
```

```
A5

A6 = np.array(A[15:18,:])
A6

A7 = np.array(A[18:21,:])
A7

A8 = np.array(A[21:24,:])
A8

A9 = np.array(A[24:27,:])
A9

A10 = np.array(A[27:30,:])
A10

A11 = np.array(A[30:33,:])
A11

A12 = np.array(A[33:36,:])
A12

A13 = np.array(A[36:39,:])
A13


A14 = np.array(A[39:42,:])
```

```
A14

A15 = np.array(A[42:45,:])
A15

A16 = np.array(A[45:48,:])
A16

A17 = np.array(A[48:51,:])
A17

A18 = np.array(A[51:54,:])
A18

A19 = np.array(A[54:57,:])
A19

A20 = np.array(A[57:60,:])
A20

A21 = np.array(A[60:63,:])
A21

A22 = np.array(A[63:66,:])
A22


A23 = np.array(A[66:69,:])
```

```
A23


A24 = np.array(A[69:72,:])
A24


A25 = np.array(A[72:75,:])
A25


A26 = np.array(A[75:78,:])
A26


A27 = np.array(A[78:81,:])
A27


A28 = np.array(A[81:84,:])
A28


A29 = np.array(A[84:87,:])
A29


Combo_i = []
for i in range(10):

Combo_i.append(np.array([randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),randint(0,2),]))
SOC = np.asarray(Combo_i)
print SOC
```

```
np.size(SOC)


Wt = input('Enter the importance factor for Time:')
Wc = input('Enter the importance factor for Cost:')
Wcr = input('Enter the importance factor for Credits:')


 import copy


def
fitness_function(A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,A12,A13,A14,A15,A16,A17,A18,A1
9,A20,A21,A22,A23,A24,A25,A26,A27,A28,A29,SOC):
    Time_Sum_j = []
    Cost_Sum_j = []
    MR1_Sum_j = []
    MR2_Sum_j = []
    MR3_Sum_j = []
    Total_Cr_j = []


    for j in range(SOC.shape[0]):
        Solution_j =
np.array([A1[SOC[j,0]],A2[SOC[j,1]],A3[SOC[j,2]],A4[SOC[j,3]],A5[SOC[j,4]],A6[SOC[j,5]],
A7[SOC[j,6]],A8[SOC[j,7]],A8[SOC[j,7]],A9[SOC[j,8]],A10[SOC[j,9]],A11[SOC[j,10]],A12[S
OC[j,11]],A13[SOC[j,12]],A14[SOC[j,13]],A15[SOC[j,14]],A16[SOC[j,15]],A17[SOC[j,16]],A
18[SOC[j,17]],A19[SOC[j,18]],A20[SOC[j,19]],A21[SOC[j,20]],A22[SOC[j,21]],A23[SOC[j,2
2]],A24[SOC[j,23]],A25[SOC[j,24]],A26[SOC[j,25]],A27[SOC[j,26]],A28[SOC[j,27]],A29[SO
C[j,28]]])
        Time_Sum_j.append(np.sum(Solution_j[:,0]))
        Cost_Sum_j.append(np.sum(Solution_j[:,1]))


        Cost_Sum = np.sum(Solution_j[:,1])
        MR1_Sum = np.sum(Solution_j[:,2])
```

```
    MR2_Sum = np.sum(Solution_j[:,3])
    MR3_Sum = np.sum(Solution_j[:,4])


#MR2_Sum_j.append(np.sum(Solution_j[:,3]))
#MR3_Sum_j.append(np.sum(Solution_j[:,4]))

    Perc_MR1 = (float(MR1_Sum)/float(Cost_Sum))*100

    Perc_MR2 = (float(MR2_Sum)/float(Cost_Sum))*100

    Perc_MR3 = (float(MR3_Sum)/float(Cost_Sum))*100

    if ((Perc_MR1>=10) & (Perc_MR1<20)):
        Cr1 = 1
    elif Perc_MR1>=20:
        Cr1 = 2
    else:
        Cr1 = 0


    if ((Perc_MR2>=10) & (Perc_MR2<20)):
        Cr2 = 1
    elif Perc_MR2>=20:
        Cr2 = 2
    else:
        Cr2 = 0
```

```
        if (Perc_MR3>=2.5):
            Cr3 = 1
        else:
            Cr3 = 0

        Total_Cr_j.append(Cr1+Cr2+Cr3)



    TimeSum = np.asarray(Time_Sum_j)
    CostSum = np.asarray(Cost_Sum_j)
    CreditSum = np.asarray(Total_Cr_j)

    Mat = np.vstack(((TimeSum,CostSum),CreditSum))
    Final_Mat = np.transpose(Mat.astype(float))

# All numbers are normalized by dividing them by the maximum. This is because every element being divided is a sum for one combination.

    p = np.max(TimeSum)
    q = np.max(CostSum)
    r = np.max(CreditSum)

    Norm_Time = Final_Mat[:,0]/float(p)
    Norm_Cost = Final_Mat[:,1]/float(q)
    Norm_Credit = Final_Mat[:,2]/float(r)

    Norm = np.vstack(((Norm_Time,Norm_Cost),Norm_Credit))
    Normalized_Mat = np.transpose(Norm)
```

```
    Fitness_k = []
    for k in range(SOC.shape[0]):
        Fitness_k.append(-Normalized_Mat[k,0]*(float(Wt)/(Wt+Wc+Wcr)) -
Normalized_Mat[k,1]*(float(Wc)/(Wt+Wc+Wcr)) +
Normalized_Mat[k,2]*(float(Wcr)/(Wt+Wc+Wcr)))

    Fitval = np.asarray(Fitness_k)
    Fitness_Values = np.transpose(Fitval)
    Max_Fit = np.max(Fitness_Values)
    return (Max_Fit,Fitness_Values,CreditSum)



for i in  range(1000):
    #pdb.set_trace()
    #print ("iteration no.",i)
    Max_Fit,Fitness_Values,CreditSum =
fitness_function(A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,A12,A13,A14,A15,A16,A17,A18,A1
9,A20,A21,A22,A23,A24,A25,A26,A27,A28,A29,SOC)

    m = np.argmax(Fitness_Values)

    #Mutation
    pos_to_mutate = randint(0,len(SOC[m,:])-1)

    New_SOC=np.array(copy.copy(SOC[m,:]))
    New_SOC[pos_to_mutate]=randint(0,2)

    SOC = np.vstack((SOC,New_SOC))
```

```
    Max_Fit,Fitness_Values,CreditSum =
fitness_function(A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,A12,A13,A14,A15,A16,A17,A18,A1
9,A20,A21,A22,A23,A24,A25,A26,A27,A28,A29,SOC)

    min = np.argmin(Fitness_Values)

    Fitness_Values[min]

    if Fitness_Values[SOC.shape[0]-1]>=Fitness_Values[min]:
        SOC = np.delete(SOC,min,0)

    else:
        SOC = np.delete(SOC,SOC.shape[0]-1,0)

    Max_Fit,Fitness_Values,CreditSum =
fitness_function(A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,A12,A13,A14,A15,A16,A17,A18,A1
9,A20,A21,A22,A23,A24,A25,A26,A27,A28,A29,SOC)

    #Start of crossover
    x = np.argmax(Fitness_Values)

    New_Fitness_Values = np.array(copy.copy(Fitness_Values))

    New_Fitness_Values = np.delete(New_Fitness_Values,x,0)

    y = np.argmax(New_Fitness_Values)

    if y>x:
        y = y+1
```

```
pos_to_crossover = randint(0,len(SOC[x,:]))

l = len(SOC[x,:])

child1 = np.concatenate((SOC[x,0:pos_to_crossover],SOC[y,pos_to_crossover:l]),axis=0)
child2 = np.concatenate((SOC[y,0:pos_to_crossover],SOC[x,pos_to_crossover:l]),axis=0)

SOC = np.vstack((SOC,child1,child2))

Max_Fit,Fitness_Values,CreditSum = fitness_function(A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,A12,A13,A14,A15,A16,A17,A18,A19,A20,A21,A22,A23,A24,A25,A26,A27,A28,A29,SOC)

min = np.argmin(Fitness_Values)

SOC = np.delete(SOC,min,0)

Max_Fit,Fitness_Values,CreditSum = fitness_function(A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,A12,A13,A14,A15,A16,A17,A18,A19,A20,A21,A22,A23,A24,A25,A26,A27,A28,A29,SOC)

min = np.argmin(Fitness_Values)

SOC = np.delete(SOC,min,0)

Max_Fit,Fitness_Values,CreditSum = fitness_function(A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,A12,A13,A14,A15,A16,A17,A18,A19,A20,A21,A22,A23,A24,A25,A26,A27,A28,A29,SOC)

max = np.argmax(Fitness_Values)
```

```
Optimal_Solution = []

Optimal_Solution = np.array([A1[SOC[max,0]],A2[SOC[max,1]],A3[SOC[max,2]],A4[SOC[max,3]],A5[SOC[max,4]],A6[SOC[max,5]],A7[SOC[max,6]],A8[SOC[max,7]],A9[SOC[max,8]],A10[SOC[max,9]],A11[SOC[max,10]],A12[SOC[max,11]],A13[SOC[max,12]],A14[SOC[max,13]],A15[SOC[max,14]],A16[SOC[max,15]],A17[SOC[max,16]],A18[SOC[max,17]],A19[SOC[max,18]],A20[SOC[max,19]],A21[SOC[max,20]],A22[SOC[max,21]],A23[SOC[max,22]],A24[SOC[max,23]],A25[SOC[max,24]],A26[SOC[max,25]],A27[SOC[max,26]],A28[SOC[max,27]],A29[SOC[max,28]]])

Optimal_Solution


np.shape(Optimal_Solution)


np.sum(Optimal_Solution[:,0])


np.sum(Optimal_Solution[:,1])


CreditSum[m]
```

Appendix C – HMC Case study Full Dataset

Activity Name	Material	DAM	Cost ($)	MR1	MR2	MR3
Concrete	Material 1	30	154900	$0.00	$125,469.00	$0.00
	Material 2	28	376533	$16,907.00	$376,533.00	$0.00
	Material 3	27	337036	$15,167.00	$337,036.00	$0.00
Concrete - Cast in Place	Material 1	25	218656	$0.00	$218,656.00	$0.00
	Material 2	20	564799	$25,360.00	$564,799.00	$0.00
	Material 3	23	505554	$22,750.00	$505,554.00	$0.00
Rebar - Cast in Place	Material 1	20	238257	$218,006.00	$238,257.00	$0.00
	Material 2	20	795710	$698,633.00	$795,710.00	$0.00
	Material 3	20	901804	$844,089.00	$901,804.00	$0.00
Pre-Cast	Material 1	24	261962	$246,245.00	$167,656.00	$0.00
	Material 2	22	200000	$183,000.00	$200,000.00	$0.00
	Material 3	24	198000	$181,170.00	$198,000.00	$0.00
Cold Formed Metal Framing	Material 1	5	196600	$70,776.00	$68,810.00	$0.00
	Material 2	4	250000	$75,000.00	$250,000.00	$12,500.00
	Material 3	4	250984	$75,296.00	$250,984.00	$0.00
Sheathing	Material 1	13	23684	$0.00	$22,263.00	$0.00
	Material 2	10	74716	$0.00	$74,716.00	$0.00
	Material 3	9	42843	$1,778.00	$0.00	$86.00
	Material 1	40	174267	$54,023.00	$0.00	$0.00

Interior Non-Load Bearing Steel	Material 2	37	170000	$52,700.00	$170,000.00	$8,500.00
	Material 3	38	180000	$55,800.00	$180,000.00	$0.00
CertainTeed Ceiling Grid "Z" Furring	Material 1	43	13722	$0.00	$0.00	$0.00
	Material 2	40	13722	$0.00	$0.00	$0.00
	Material 3	42	15000	$0.00	$15,000.00	$0.00
Gypsum board	Material 1	45	254382	$35,614.00	$244,207.00	$0.00
	Material 2	40	80997	$6,075.00	$80,997.00	$0.00
	Material 3	41	128814	$4,509.00	$128,814.00	$387.00
Drywall Alum End Cap	Material 1	1	4000	$3,580.00	$0.00	$0.00
	Material 2	1	420	$376.00	$420.00	$0.00
	Material 3	1	303	$271.00	$303.00	$0.00
Gypsum Board - Shaft	Material 1	5	25000	$750.00	$25,000.00	$0.00
	Material 2	4	7961	$598.00	$7,961.00	$0.00
	Material 3	5	12660	$444.00	$12,660.00	$38.00
American Gypsum Firebloc X	Material 1	29	162475	$8,124.00	$162,475.00	$0.00
	Material 2	25	54850	$1,591.00	$54,850.00	$3,182.00
	Material 3	26	54850	$2,249.00	$54,850.00	$110.00
	Material 1	42	20548	$6,165.00	$0.00	$0.00

Sound Attenuation Batt Insulation	Material 2	40	25000	$9,375.00	$25,000.00	$0.00
	Material 3	41	28650	$15,185.00	$0.00	$860.00
	Material 1	38	32399	$26,568.00	$0.00	$0.00
Aluminum Column Covers [Alloy 5052]	Material 2	36	127253	$37,540.00	$127,253.00	$0.00
	Material 3	37	143159	$12,341.00	$143,159.00	$0.00
	Material 1	1	1985	$318.00	$1,906.00	$0.00
Mbloc Abuse Resistant Board	Material 2	1	1333	$708.00	$0.00	$0.00
	Material 3	1	1341	$366.00	$0.00	$3.00
	Material 1	23	10790	$1,457.00	$0.00	$0.00
Roxul AFB	Material 2	22	12000	$4,500.00	$12,000.00	$0.00
	Material 3	22	50224	$8,036.00	$47,713.00	$0.00
	Material 1	3	4500	$1,373.00	$4,500.00	$0.00
Resin Panels	Material 2	3	4000	$1,260.00	$4,000.00	$80.00
	Material 3	3	5500	$1,733.00	$5,500.00	$0.00
	Material 1	50	117086	$35,126.00	$117,086.00	$0.00
Anchored Stone Veneer	Material 2	48	125000	$37,500.00	$125,000.00	$0.00
	Material 3	46	130000	$39,000.00	$130,000.00	$0.00
	Material 1	75	2273579	$1,751,284.00	$31,346.00	$0.00

Steel	Material 2	71	2273579	$1,751,284.00	$31,346.00	$0.00
	Material 3	70	2273579	$1,751,284.00	$31,346.00	$0.00
Wood Veneer Faced Architectural Cabinets	Material 1	55	94069	$47,035.00	$0.00	$0.00
	Material 2	50	100000	$55,000.00	$0.00	$5,000.00
	Material 3	53	103500	$56,925.00	$0.00	$0.00
Alum Storefront & Window Frames	Material 1	30	1103620	$568,365.00	$0.00	$0.00
	Material 2	28	1151620	$593,085.00	$0.00	$0.00
	Material 3	30	1200000	$624,000.00	$0.00	$24,000.00
Metal Lockers	Material 1	8	71880	$44,566.00	$0.00	$0.00
	Material 2	7	65000	$40,300.00	$65,000.00	$3,250.00
	Material 3	8	65000	$19,500.00	$65,000.00	$0.00
Toilet partitions	Material 1	9	0	$0.00	$0.00	$0.00
	Material 2	8	0	$0.00	$0.00	$0.00
	Material 3	8	0	$0.00	$0.00	$0.00
HM Doors & Frames	Material 1	61	71511	$14,303.00	$0.00	$0.00
	Material 2	60	71511	$14,303.00	$0.00	$0.00
	Material 3	58	75000	$15,000.00	$0.00	$750.00
ACM Panels	Material 1	17	14599	$6,570.00	$0.00	$0.00
	Material 2	15	57340	$16,916.00	$57,340.00	$0.00

	Material 3	14	64508	$5,561.00	$64,508.00	$0.00
Flooring-Carpet	Material 1	39	154564	$48,688.00	$0.00	$0.00
	Material 2	35	140000	$52,500.00	$140,000.00	$0.00
	Material 3	38	160000	$56,000.00	$160,000.00	$0.00
Flooring-Resilient	Material 1	26	30406	$5,170.00	$0.00	$0.00
	Material 2	25	151868	$25,818.00	$151,868.00	$0.00
	Material 3	26	151414	$25,741.00	$151,414.00	$0.00
Flooring-Tile	Material 1	16	68414	$11,973.00	$0.00	$0.00
	Material 2	14	86242	$15,093.00	$86,242.00	$0.00
	Material 3	12	86304	$15,104.00	$86,304.00	$0.00
Flooring-Rubber Base	Material 1	21	20608	$1,443.00	$0.00	$0.00
	Material 2	19	20608	$1,443.00	$20,608.00	$0.00
	Material 3	21	20608	$1,443.00	$20,608.00	$0.00

Appendix D – Fire Station Full Dataset

Activity		DAM (days)	Cost	MR1	MR2	MR3
Concrete - Cast in Place	Material 1	10	$93,008.00	$0.00	$93,008.00	$0.00
	Material 2	8	$100,000.00	$14,000.00	$100,000.00	$5,800.00
	Material 3	7	$56,326.00	$14,082.00	$56,326.00	$4,281.00
Rebar - Cast in Place	Material 1	3	$7,368.00	$6,742.00	$7,368.00	$0.00
	Material 2	3	$10,000.00	$9,700.00	$10,000.00	$0.00
	Material 3	3	$8,265.00	$10,125.00	$8,265.00	$521.00
Pre-Cast	Material 1	4	$134,422.00	$126,357.00	$86,030.00	$0.00
	Material 2	4	$120,000.00	$112,800.00	$102,000.00	$0.00
	Material 3	5	$150,326.00	$139,052.00	$0.00	$6,765.00
Cold Formed Metal Framing	Material 1	15	$14,500.00	$5,220.00	$5,075.00	$0.00
	Material 2	20	$14,500.00	$5,438.00	$7,975.00	$0.00
	Material 3	10	$16,326.00	$4,898.00	$0.00	$2,580.00
Sheathing	Material 1	12	$19,395.00	$0.00	$18,231.00	$0.00
	Material 2	8	$25,000.00	$28,125.00	$23,750.00	$0.00
	Material 3	6	$11,236.00	$9,551.00	$0.00	$292.00
Interior Non-Load Bearing Steel	Material 1	20	$3,177.00	$985.00	$0.00	$0.00
	Material 2	15	$1,000.00	$460.00	$150.00	$0.00
	Material 3	11	$6,258.00	$1,877.00	$0.00	$812.00

Gypsum board	Material 1	18	$25,712.00	$3,600.00	$24,683.00	$0.00
	Material 2	10	$20,000.00	$27,500.00	$20,000.00	$1,200.00
	Material 3	15	$30,236.00	$43,842.00	$30,236.00	$4,052.00
Steel	Material 1	7	$98,126.00	$75,557.00	$1,472.00	$0.00
	Material 2	5	$85,625.00	$65,931.00	$72,781.00	$12,844.00
	Material 3	8	$98,126.00	$63,782.00	$98,126.00	$0.00
Wood Veneer Faced Architectural Cabinets	Material 1	5	$21,458.00	$10,729.00	$0.00	$0.00
	Material 2	6	$30,000.00	$18,000.00	$0.00	$6,000.00
	Material 3	5	$16,326.00	$17,550.00	$16,326.00	$0.00
Metal Lockers	Material 1	4	$13,910.00	$8,624.00	$0.00	$0.00
	Material 2	4	$10,259.00	$6,361.00	$0.00	$0.00
	Material 3	3	$13,910.00	$7,998.00	$13,910.00	$0.00
HM Doors & Frames	Material 1	8	$128,914.00	$25,783.00	$0.00	$0.00
	Material 2	8	$125,653.00	$30,157.00	$0.00	$0.00
	Material 3	9	$130,548.00	$31,332.00	$130,548.00	$2,872.00
Flooring-Carpet	Material 1	3	$87,984.00	$27,715.00	$0.00	$0.00
	Material 2	4	$75,321.00	$7,532.00	$48,959.00	$2,636.00
	Material 3	3	$87,984.00	$21,996.00	$0.00	$8,886.00
Flooring-Resilient	Material 1	4	$4,377.00	$744.00	$0.00	$0.00
	Material 2	4	$5,326.00	$1,332.00	$3,462.00	$154.00

	Material 3	4	$6,236.00	$3,118.00	$0.00	$1,253.00
Flooring-Tile	Material 1	5	$5,565.00	$974.00	$0.00	$0.00
	Material 2	2	$4,562.00	$912.00	$2,965.00	$274.00
	Material 3	3	$4,258.00	$852.00	$0.00	$0.00
Flooring-Rubber Base	Material 1	6	$3,804.00	$266.00	$0.00	$0.00
	Material 2	8	$4,256.00	$0.00	$2,979.00	$426.00
	Material 3	6	$2,456.00	$0.00	$0.00	$246.00