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Single Tower Crane Allocation Models Using Ant Colony Optimization

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SINGLE TOWER CRANE ALLOCATION MODELS

USING ANT COLONY OPTIMIZATION

A Thesis

by

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ABSTRACT

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The construction industry greatly benefits from the utilization of heavy machines and equipment to accomplish successful projects. Tower cranes, in specific, have a crucial role in the transportation of material loads across the site. Because these machines are fixed to the ground, it is essential for planners and managers to position them in a location that provides the most efficient transfer of materials possible. This is commonly known as the tower crane allocation problem, and many researchers have attempted to optimize the tower crane location using mathematical, artificial intelligence, and simulation approaches. However, many works from the literature contain critical errors which make the models infeasible. This research presents the application of ant colony optimization (ACO) and an ACO variation to tower crane allocation models. Results show that the approaches presented in this work are up to par with even the most powerful methodologies used to solve the problem.

DEDICATION

This work is dedicated to all those who believed in this research and in my potential to achieve such work. Thank you; this was possible because to you.

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CHAPTER I

INTRODUCTION

Background and Overview

Ever since the beginning of the 20th century the construction industry has adopted many different types of techniques and machinery to achieve successful projects. From backhoes and excavators to bulldozers and tower cranes, all these heavy equipment machines have found their place on construction sites. Tower cranes, in particular, have become heavily depended on and essential equipment needed for large construction projects. These towers are tall structures used for the transportation of materials across the site.

Tower Crane Composition and Variations

In general, tower cranes are composed of eight basic elements: a base, mast, working arm, machinery arm, trolley, counter weights, slewing unit, and a cabin. The base of the crane is typically anchored to a concrete foundation or mounted with concrete ballast to resist the overturning moments. The mast is the vertical component that provides height to the crane, and it is composed of several segments put together by smaller cranes. The working arm, also known as jib or boom, makes up the horizontal component of the crane where the trolley is found. The trolley is used to move loads closer to the mast or further and represents the radial component of movement of the crane. The machinery arm is located opposite to the jib and holds the weight needed to counter the effects of the load imposed by the working arm. This counter weight typically comes in the form of concrete ballast. Further, this machinery arm is also a place for the power plant, hoist unit, and control panels (Shapiro, Shapiro, & Shapiro, 2010). The slewing unit gives rotation capabilities to the crane. This provides the angular component of movement and can be found on the top of the mast or bottom, creating a top slewing tower crane configuration or bottom slewer respectively. Lastly, the operator's cabin is the place where the individual in charge of commanding the crane is situated. Generally, the cabin is found at the top of the crane to allow complete visibility of the site to the operator, but its position can change depending on the crane manufacturer. An illustration showing the general components discussed can be seen in Figure 1.

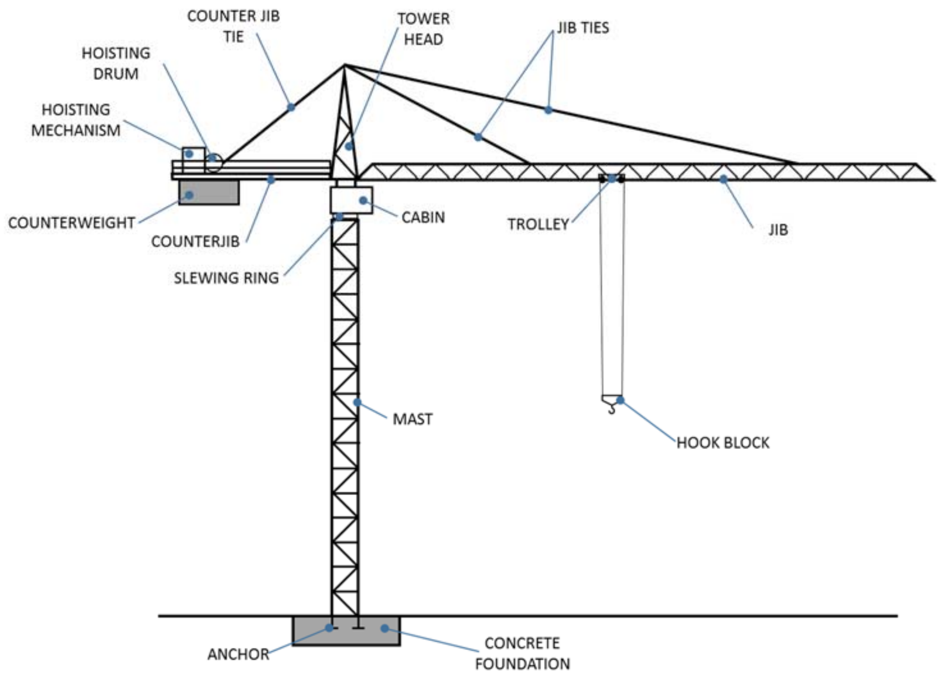
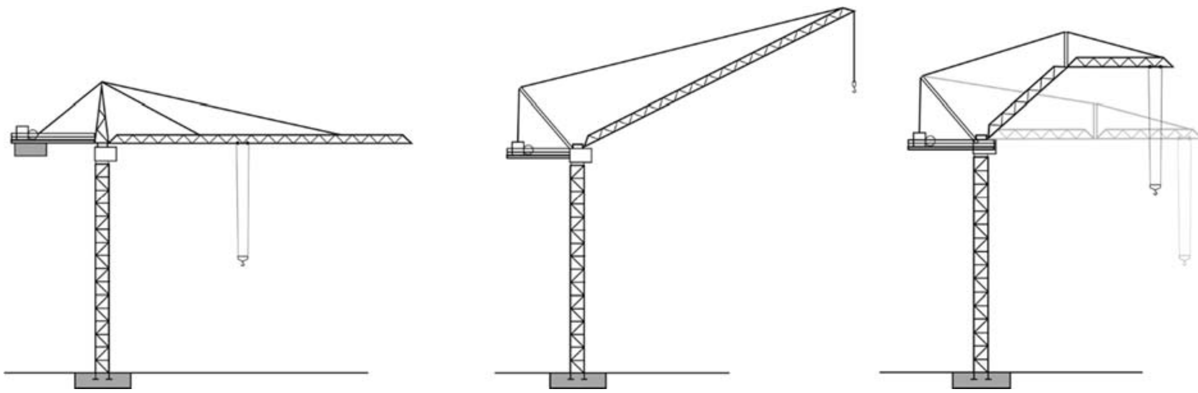


Figure 1. Tower Crane Components

Over the years, changes and modification to the basic components of the crane have been made to enhance the crane's performance in different situations. The basic, horizontal boom – known as a hammerhead boom – can be mounted with a pivot to allow it to rise to greater heights. This configuration is known as a luffing boom and trolleys are commonly missing on this type of boom. Another jib variation is the articulated jib where the pivot is found in the middle of the jib to allow both a trolley and different inclinations. In addition, this configuration offers the crane the ability to maneuver and pass over different types of obstructions (Shapiro et al. 2010). Figure 2 illustrates the three different jib configurations just discussed.



a. Hammerhead b. Luffing c. Articulated boom

Figure 2. Tower Crane Boom Configurations

An additional type of configuration available to the crane is the self-erecting system. This system is composed of an additional mast section equipped with hydraulic jacks. The section is placed over the existing mast segments before the top of the crane is installed. Once done so, the crane uses its boom to hold a mast segment in place while the jacks push the crane assembly up. When there is enough space, the trolley moves the mast segment in to get installed and the process continues until the desired height is reached.

Tower Crane Advantages and Allocation Problem

Due to their construction and design, these machines are able to provide superior load carrying capacities that other construction equipment cannot. In addition, these towers can lift and deliver material loads at higher altitudes while saving great amounts of space on site.

Despite its advantages, these cranes are associated with high costs in the form of rental, installation, and set-up fees. Further, their design limits their mobility and prevents them to be moved from the location where they are situated. Thus, it is important for managers and planners to place tower cranes at a location that will provide the most efficient transfer of materials possible. This is known as the tower crane allocation problem, where the objective is to maximize the usage of the crane by situating it at a location that minimizes the total time of material transportation or total costs.

Research Objectives and Methodology

Many studies have attempted to optimize the tower crane location with a wide variety of techniques and success. However, many of the studies and models in the literature contain important flaws in the form of formulation errors, discrepancies, and issues that affect their use by industry professionals and researchers. In addition, powerful optimization techniques such as Ant Colony Optimization (ACO), have rarely been employed as means of optimization for this problem. Furthermore, the literature contains some tower crane allocation problems that present special challenges and difficulties even to an ACO tower crane model.

Therefore, the objectives of this research include 1) the reconstruction of models from the literature, 2) the implementation of ACO to the reconstructed models as means of optimization, and 3) the development and application of a modified ACO approach tailored to solve special type of tower crane allocation problems from the literature.

In order to achieve the aforementioned objectives, the literature review pertaining to the topic was carefully reviewed. Past models were analyzed and discrepancies, errors, and issues were documented. The sources of error were found and addressed, and the models were reconstructed to account for these changes. ACO was applied to the reconstructed models, noting the performance against the original methodologies, as well as the developed variation called Modified Ant Colony Approach (MACA). Results were gathered and concluding remarks were made.

Thesis Structure

The organization of this thesis begins with an introduction and discussion of the literature on Chapter 2. Chapter 3 present the ACO approach to the tower crane allocation models from the literature. Chapter 4 exhibits the modified ACO approach for the allocation problem. Finally, Chapter 5 concludes the findings and results of this research.

CHAPTER II

LITERATURE REVIEW

The single tower crane allocation problem revolves around finding the best location for a tower crane such that the total travel time or total costs are minimized. Over the last three decades, many studies have made contributions to the optimization of tower crane location in distinct ways. This chapter will present the works pertaining to this problem in two main sections that relate to their methods of optimization: mathematical models and optimization and artificial intelligence. The works will be presented by discussing their contributions followed by an elaboration of their weaknesses and limitations. Furthermore, a tower crane background section will present useful information pertaining to the crane's performance and factors that influence it.

Tower Crane Performance

As discussed in the previous chapter, the tower crane is composed of eight basic elements that assist the crane in accomplishing its many tasks. Nevertheless, there are many factors that affect the performance of the tower crane. Such factors include the power of the motors, length of the jib, crane height, site and weather conditions, crane's lifting capacity, and multiple tower cranes on site. All these conditions affect important parameters that influence the tower crane performance, and these parameters can be encompassed into five categories:

1. Radial Movement. The radial movement is the movement of the hook as it travels on the trolley along the jib. This movement is composed of the traveled distance of the trolley

from one point to the other, generally seen as ρ, at a certain velocity, V_R. Figure 3 shows the trolley path for two distinct boom positions. The works that accounted for the radial movement of the crane include Rodriguez-Ramos and Francis (1983), Choi and Harris (1991), Zhang, Harris, and Olomolaiye (1996), Zhang, Harris, Olomolaiya, and Hold (1999), Tam, Tong, and Chang (2001), Alkriz and Mangin (2005), Huang, Wong, and Tam (2011), Abdel-Khalel, Shawki, and Adel (2013), Lien and Cheng (2014), Zavichi, Madani, Xanthopoulos, and Oloufa (2014), Abdelmegid, Shawki, and Abdel-Khalek (2015), Lee, Lim, Cho, and Kang (2015), Wang et al. (2015), Monghasemi, Nikoo, and Adamowski (2016), Tubaileh (2016), and Moussavi Nadoushani, Hammad, and Akbarnezhad (2016).

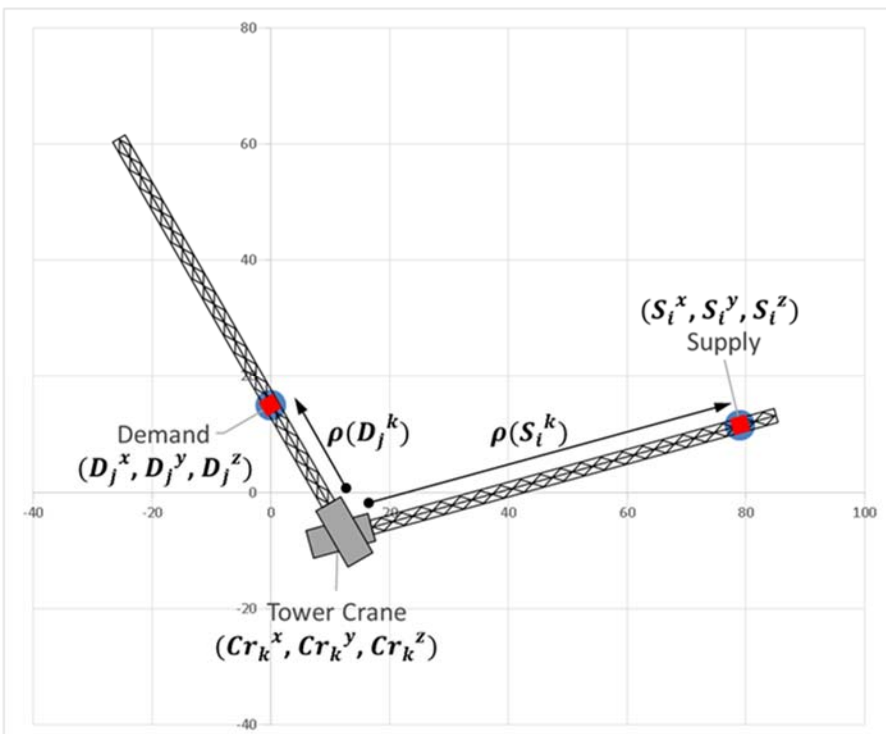


Figure 3. Trolley Positions In Radial Motion

2. Angular Movement. The angular or tangential movement occurs when the crane rotates from one facility to the other. This angular movement is described in terms of the angular

distance, θ, between two points and the angular velocity, $V\omega$, used to move between them. In Figure 4, the angular movement between a supply and demand pair is depicted by parameter ω. Papers such as Rodriguez-Ramos and Francis (1983), Choi and Harris (1991), Zhang et al. (1996), Zhang et al. (1999), Tam et al. (2001), Tam and Tong (2003), Alkriz and Mangin (2005), Huang et al. (2011), Abdel-Khalek et al. (2013), Lien and Cheng (2014), Zavichi et al. (2014), Abdelmegid et al. (2015), Wang et al. (2015), Lee et al. (2015), Monghasemi et al. (2016), Tubaileh (2016), Moussavi Nadoushani et al. (2016) discussed the usage of these parameters in their models.

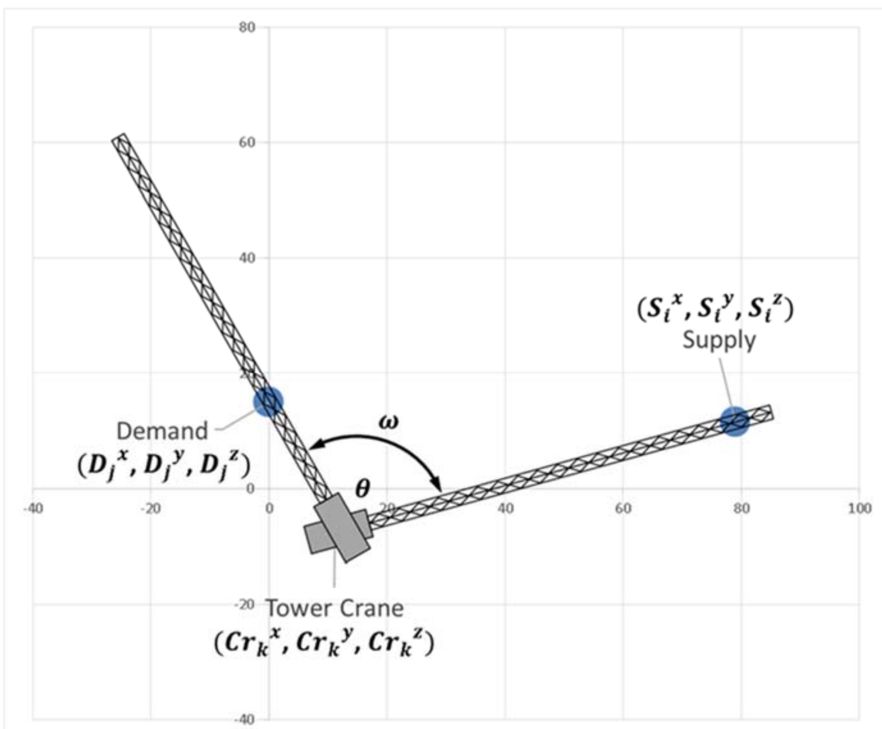


Figure 4. Angular Movement From Two Positions

3. Vertical Movement. The hoisting and lowering actions represent the vertical movement that is performed by the crane. This vertical movement is characterized by the vertical displacement of the hook, generally notated as ΔZ, and the hoisting velocity of the crane, V_H. As an example, Figure 5 illustrates two vertical hook positions and the resulting

displacement. Zhang et al. (1999), Tam et al. (2001), Alkriz and Mangin (2005), Huang et al. (2011), Abdel-Khalek et al. (2013), Lien and Cheng (2014), Zavichi et al. (2014), Abdelmegid et al. (2015), Wang et al. (2015), Lee et al. (2015), Monghasemi et al. (2016), Tubaileh (2016), and Moussavi Nadoushani et al. (2016) implemented the vertical movement in terms of time in their models.

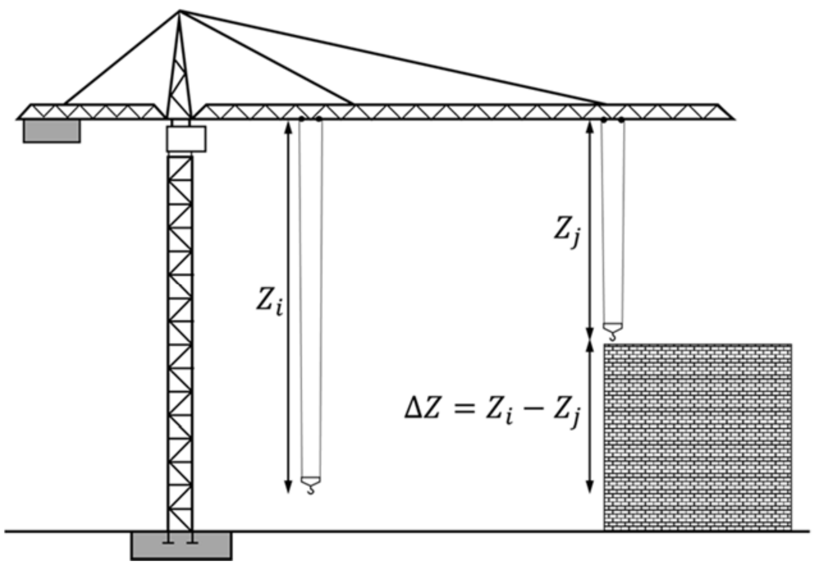


Figure 5. Crane Hoisting Movement

4. Quantity of material, Q. The amount of material in need of transportation affects how frequent the crane travels to and from the facilities as well as the material load to be handled. Choi and Harris (1991), Zhang et al. (1996), Zhang et al. (1999), Tam et al. (2001), Tam and Tong (2003), Huang et al. (2011), Wang et al. (2015), and Moussavi Nadoushani et al. (2016) accounted for the amount of material transported between facilities.

5. Planar coordination parameters α and β. The α and β parameters are factors that describe how the crane movement occurs in the horizontal or vertical planes. For instance, parameter α describes how simultaneous or consecutive the crane hook moves radially

and angularly along the horizontal plane. In Figure 6, this description can be seen by picturing the trolley moving towards the mast at velocity V_R while rotating towards the demand point along path ω. In contrast, β considers how simultaneous or consecutive the hook movement is along the vertical and horizontal planes. This would consider the horizontal plane movements previously discussed, with the addition of lowering or raising the crane hook. For both parameters, values closer to "1" represent the extreme scenario of full consecutive movement while a value of "0" depicts full simultaneous movement (Zhang et al., 1999). Other works that used these parameters include Zhang et al. (1996), Zhang et al. (1999), Tam et al. (2001), Alkriz and Mangin (2005), Huang et al. (2011), Abdel-Khalek et al. (2013), Lien and Cheng (2014), Zavichi et al. (2014), Abdelmegid et al. (2015), Wang et al. (2015), Monghasemi et al. (2016), Tubaileh (2016), and Moussavi Nadoushani et al. (2016).

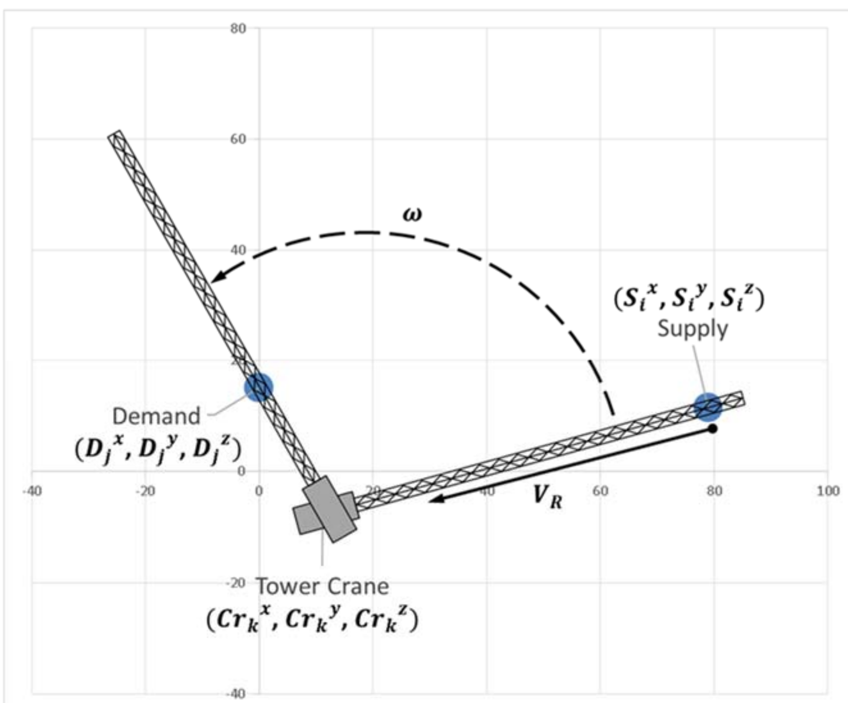


Figure 6. Combined Angular And Radial Motions In Horizontal Plane

6. Hook movement difficulty parameter γ. Factor γ accounts for the complications that might hinder the operator from performing crane operations at their best possible condition. Such conditions can include weather conditions, such as foggy weather that affects visibility, and site conditions, such has nearby buildings causing obstruction in site and operation. Huang et al. (2011), Zavichi et al. (2014), Monghasemi et al. (2016), and Moussavi Nadoushani et al. (2016) included this factor when determining the total travel time of the hook.

The above-mentioned parameters form part of the systems that affect the performance of the tower crane. In the next sections, research works from the literature will be presented, along with their contributions, limitations, and the manner in which they considered the afore-mentioned parameters in their models.

Mathematical Models

The first work in this section and to contribute to this topic was done by Walter Rodriguez-Ramos and Richard Francis in 1983. The authors were the first to propose a mathematical model that accounted for the minimum angular and radial movements of the crane's hook in terms of time. The formulation for the minimum angular movement can be seen on Equation 1, where $|\theta - \theta_j|$ represents one of the possible angles created by two boom positions and $2\pi - |\theta - \theta_j|$ represents the other. As can be seen on Figure 7, when the tower crane is situated in a Cartesian coordinate system and its boom moves from one to position to another, it can do so in a clockwise or counter-clockwise motion. These two separate motions create two different angles, so the formulation accounts for selecting the minimum of the two.

$$A_j(\theta) = Min\left(|\theta - \theta_j|, 2\pi - |\theta - \theta_j|\right) \tag{1}$$

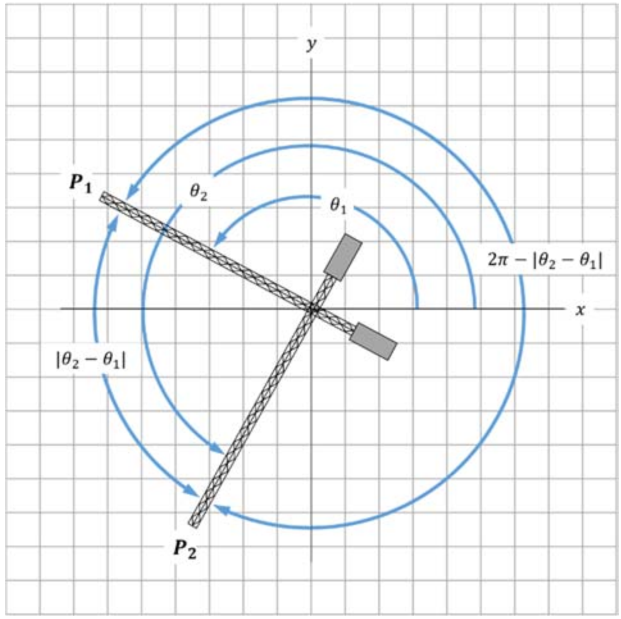


Figure 7. Tower Crane Angular Movement (Rodriguez-Ramos & Francis, 1983)

Alternatively, this calculation can be determined by envisioning the boom positions as two vectors, shown on Figure 8, and utilizing the dot product, seen in Equation 2, to determine the angle, θ, as shown in Equation 3. This approach restricts θ from 0 to π, so it will always result in the smallest angle from the two positions.

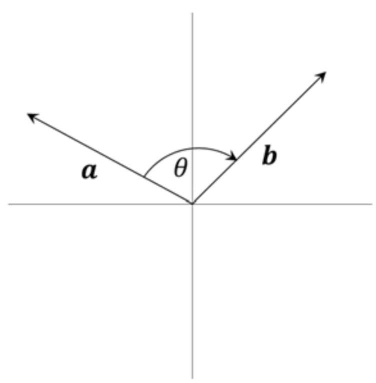


Figure 8. Crane Positions As Vectors

$$a \cdot b = |a||b|cos(\theta) \tag{2}$$

$$\theta = arccos\left(\frac{a \cdot b}{|a||b|}\right) \tag{3}$$

The radial distance was accounted by taking the difference in distance between two trolley positions as seen on Figure 9. With both angular and radial distances determined, the distances can be divided by their respective velocities to solve for a time using Equation 4, where t is the total hook time spend moving radially and angularly, V_a is the angular velocity, V_R is the radial velocity, $A_j(\theta)$ is the minimum angle, and $|r - r_j|$ is the radial distance travelled by the trolley.

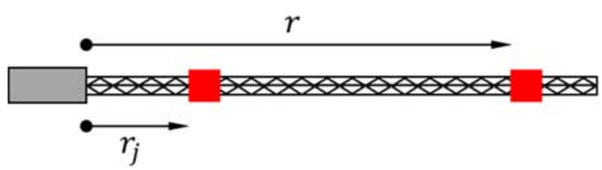


Figure 9. Radial Distance of Trolley (Rodriguez-Ramos and Francis, 1983)

$$t = \frac{A_j(\theta)}{V_a} + \frac{|r - r_j|}{V_R} \tag{4}$$

The authors' objective was to solve for the minimum total transportation costs incurred from servicing j facilities and, thus, added a cost factor, W_j, to their objective function which can be seen on Equation 5.

$$F(\theta, r) = \sum_{j=1}^{n} W_j \left(\frac{A_j(\theta)}{V_a} + \frac{|r - r_j|}{V_R} \right) \tag{5}$$

Some issues and improvements can be seen from their approach. Their model does not accurately represent the crane's movement since it accounts for the movements separately. This means that the crane moves angularly first before the trolley can perform its movement operations. This can result in greater travel time values since the angular and radial movements can occur simultaneously as the crane moves from a facility to the next. In addition, the authors provided predetermined tower crane locations in their numerical example, and their approach was used to find the best one from the set. While this might happen in real world applications, it discards other countless possible locations that may provide more optimal results.

Furusaka and Gray (1984) introduced a mathematical model that considered the type of crane used to build building floors as well as its location. The crane type decided by their model could be a mobile crane or tower crane and, when selecting a tower crane, the model had the capability of selecting multiple tower cranes to cover the whole site area. Their model attempted to find the best crane type, from a set, that could provide the least costs per building floor. In other words, their model would determine which tower crane is the most appropriate to build each building floor based on operation costs and assembly and dismantling costs (Furusaka & Gray, 1984). Despite the fact the authors considered using multiple tower cranes to ensure the coverage of the entire site area, the authors did not account for a system to check for potential collisions that could occur between the tower cranes and obstructions on site.

Choi and Harris (1991) proposed a follow up approach on their technical note. The authors accounted for the crane's hook travel time with the angular and radial concepts left behind by of Rodriguez-Ramos and Francis (1983), assumed simultaneous movement of the hook, and considered the frequency of movement that occurs when the crane moves from one facility to the next. This frequency of movement consideration was represented as a percentage of total lifts between facilities, which is described as interfacility weight (ITFW) (Choi & Harris, 1991). Every time the crane moves to a facility is considered a "lift", so the total amount of lifts for all facilities is determined to then find how frequent the crane moved from one facility to the others. Their transportation time equation can be seen on Equation 6, which is very similar to the formulation from Rodriguez-Ramos and Francis (1983) with the exception of the "2" used to represent a return movement for reloading.

$$T = 2\sum_{j=1}^{n} Max\left(\frac{A(\theta_{j-1},\theta_j)}{CAV}, \frac{|r_{j-1}-r_j|}{CRV}\right) \tag{6}$$

Choi and Harris (1991) used a construction project in Hong Kong to apply their approach using a set of pre-determined tower crane locations with Cartesian coordinates. However, just like their predecessors, they lacked accounting for other possible solutions around the project that might serve as better locations for the crane.

Zhang, Harris, and Olomolaiye (1996) provided an extensive work that utilized Monte Carlo simulation to simulate the crane's sequence of deliveries as well as a more accurate formulation of the crane's travel time. In comparison to Choi and Harris (1991), they expanded the concept of lifts into odd job requests – single lift – and batch requests (multiple lifts) (Zhang et al., 1996). These batch requests between supply and demand pairs were referred to as "lifts batch", and the deliveries are assumed to be done without interruption. Their simulation required the average number of requests – or lifts – between a supply and demand pair and their frequency in similar fashion to Choi and Harris (1991). Equations 7 and 8, respectively, were utilized for the determination of these parameters, where Q_{ij} is the total number of lifts between supply i to demand j, P is the percentage of lifts performed in batch manner, N is the number of lifts done in batch manner, and TOR is the total number of requests.

$$R_{ij} = \frac{Q_{ij}}{\sum_{k=1}^{K} P_{ij} * N_{ij}} \tag{7}$$

$$F_{ij} = \frac{R_{ij}}{\sum TOR} \tag{8}$$

Zhang et al. (1996), in addition, considered the material load being lifted on their model. This is an important consideration because loads lifted further away from the mast create higher moments on the crane. As a result, the feasible area in which the crane can reside to reach all facilities on site can be compromised. To illustrate this concept, a crane rotating 360 degrees creates a circle with its boom. This circle is the allowable reach of the crane that is dictated by the boom's length. Using each facility location as the center of this circle creates a region that is shared by all facilities such as in Figure 10. This region is known as the “feasible task area”, in which a tower crane is able to reach all facilities with its boom. However, when the maximum load to be lifted is greater on some facilities, the circle shrinks from the original span so that the crane can safely lift it. In other words, the crane offers greater load carrying capacities closer to the mast, so if the required load to be lifted is very high it would have to be lifted closer to the mast to be safely handled. For that reason, the circles shown on Figure 10 – which consider the different maximum loads per facility on the work by Zhang et al. (1996) – differ in size. This results in a more accurate representation of the feasible area where the crane needs to be located.

In similar fashion as the previous works, Zhang et al. (1996) accounted for the hook travel time using a Cartesian coordinate system. Equations 9, 10, and 11 display the linear distance between the tower crane to demand, tower crane to supply, and supply to demand points, respectively. Equation 12 and 13 are updated representations of radial and angular travel time from previous works. Equation 14 is the updated formulation that accounts for the total horizontal travel time of the hook between two facilities, where α was a factor – between “0” and “1” – used to describe the movement coordination made by the operator along the horizontal plane only. In other words, it describes the degree of how consecutive or simultaneous the movement along the horizontal plane is. A value of “0” describes complete simultaneous operation while a “1” describes full consecutive movement. Based on a study by Kogan (1976), it was noted that operators perform simultaneous crane movements 76% or the total duration of the cycle (as cited in Zhang et al., 1996). Thus, Zhang et al. (1996) used a value of 0.25 for this factor.

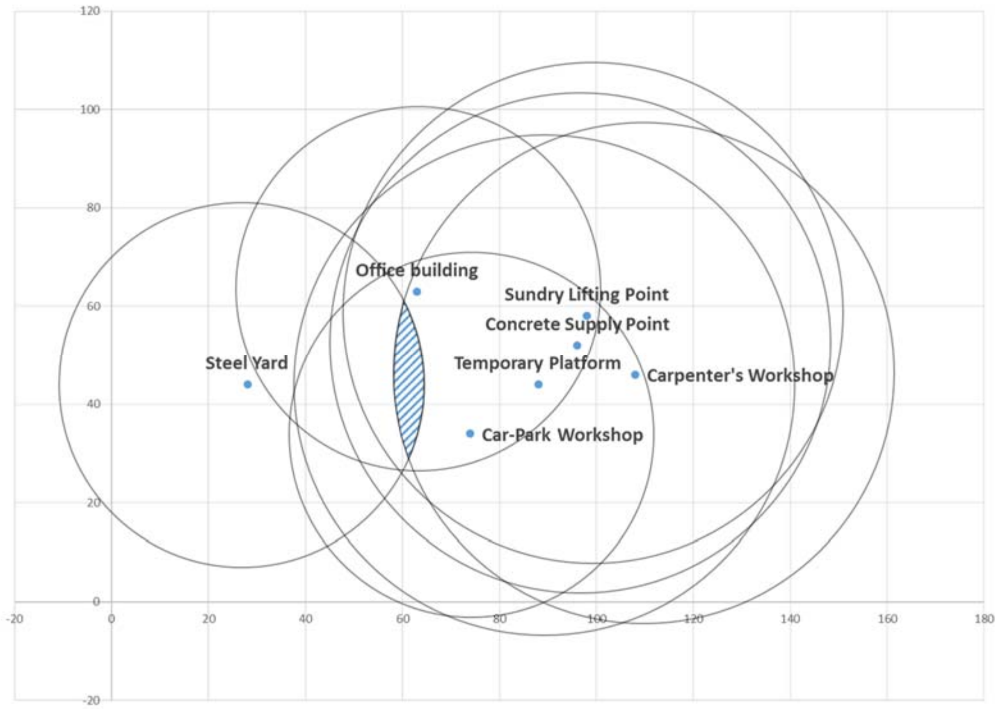


Figure 10. Feasible Task Area for Project Layout (Zhang et al., 1996)

$$\rho(D) = \sqrt{(Dx - CraneX)^2 + (Dy - CraneY)^2} \tag{9}$$

$$\rho(S) = \sqrt{(Sx - CraneX)^2 + (Sy - CraneY)^2} \tag{10}$$

$$l = \sqrt{(Dx - Sx)^2 + (Dy - Sy)^2} \tag{11}$$

$$T_a = \frac{|\rho(D) - \rho(S)|}{V_a} \tag{12}$$

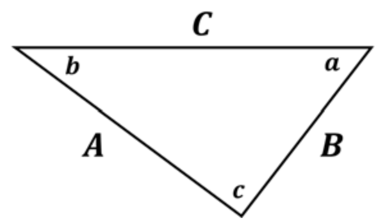
$$T_\omega = \frac{1}{\omega} * arccos\left(\frac{l^2 - (\rho(D)^2 + \rho(S)^2)}{2 * \rho(D) * \rho(S)}\right) \tag{13}$$

$$T_h = Max(T_a, T_\omega) + \alpha * Min(T_a, T_\omega) \tag{14}$$

To determine the transportation time spent on each request, Equation 15 was used by the authors, where T'_{ij} is the transportation time from last request point i to supply j, N is the number of lift in the batch, and T_{ij} is the transportation time spent from supply i to demand j.

$$TR^m = T'_{ij} + (2 * N_{ij} - 1) * T_{ij} \tag{15}$$

Despite the authors' stating a 20-40% savings in hook travel time (Zhang et al., 1996), some issues and discrepancies can be found on their work. Most notably is the incorrect mathematical formulation that accounts for the angular travel time of the hook, Equation 13. This equation is based on the cosine law to determine the angle made by the crane as it moves from one facility to the next. However, the formulation on this equation is incorrect when solving for the angle. To showcase this in detail a hypothetical example in the form of a triangle can be seen on the figure below:



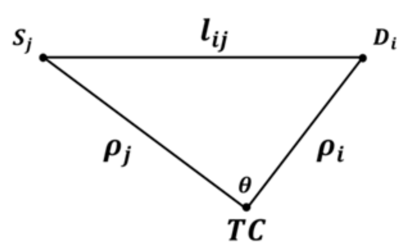
The cosine law is described as:

$$C^2 = A^2 + B^2 - 2ABcos(c)$$

Using algebraic operations, the internal angle c is determined to be:

$$c = arccos\left(\frac{A^2 + B^2 - C^2}{2AB}\right)$$

If a supply, demand, and tower crane facility take the place of the three point of the said triangle, such as:



Then the cosine law can be used to find the angle θ with respect to tower crane location $\boldsymbol{TC}$.

$$\theta = arccos\left(\frac{{\rho_j}^2 + {\rho_i}^2 - {l_{ij}}^2}{2 * \rho_j * \rho_i}\right)$$

In comparison to Equation 13, the formulation changes the signs on the numerator, which will not result in the smaller angle between two tower crane positions. This is critical since the main objective of this problem is the minimization of the total travel time of the crane. Thus, the correct formulation for the angular travel time of the hook can be seen on Equation 16. This error has been found repeatedly throughout the literature with only one exception (Abdelmegid et al., 2015).

$$T_{\omega} = \frac{1}{\omega} * arccos\left(\frac{({\rho_i}^2 + {\rho_j}^2) - {l_{ij}}^2)}{2 * \rho_j * \rho_i}\right) \tag{16}$$

An additional discrepancy found on their work that could create confusion is their batch lift and percentage of batch lift terminology. The authors provide a description for the equations, but it is not clear how the terms were applied to the simulation. If the requested job happens in batch manner the authors do not say if the batch is randomly chosen or selected in sequence until demand requirements are met. These total lift percentages have also been described as unreliable by other authors (Emsley, 2001).

A third issue is the lack of information regarding an effective algorithm used to determine the feasible area for the tower crane. Zhang et al. (1996) state utilizing this algorithm but did not show any information regarding this item in their paper.

Zhang, Harris, Olomolaiya, and Hold (1999) created an expansion to the work by Zhang et al. (1996) that accounted for locating multiple cranes. This time the authors included the vertical component of the hook travel time that was missing from previous works, which can be seen on Equation 17. This equation considered the change in vertical distance of the hook from one point to the other – seen on Figure 11 – and divided it by the vertical hoisting velocity, V_v. As a result, the total travel time of the hook formulation was updated to include parameter β as shown on Equation 18. Much like α, β describes the operator's degree of coordination between the horizontal and vertical planes. A value of "0" describes simultaneous movement and a consecutive movement is expressed by a "1". Because of safety reasons and regulations, β was assumed to be 1 for this work and many others in the future.

$$T_v = \frac{\Delta Z}{V_v} = \frac{Z_i - Z_j}{V_v} \tag{17}$$

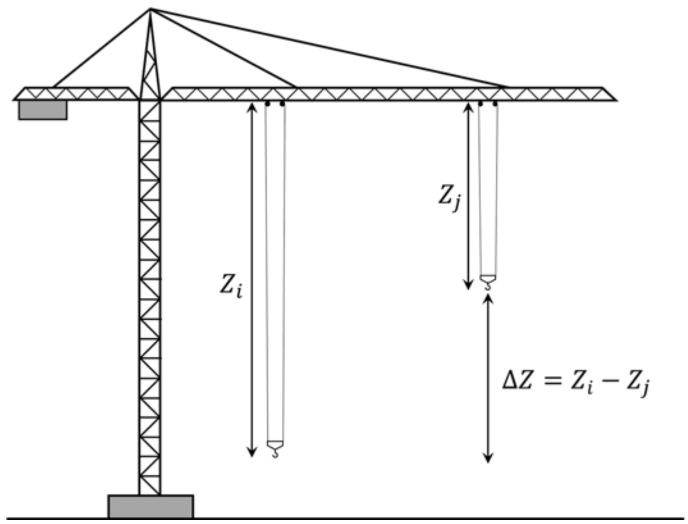


Figure 11. Vertical Distance of Hook (Zhang et al., 1999)

$$T = Max(T_h, T_v) + \beta * Min(T_h, T_v) \tag{18}$$

The authors consider the number of tower cranes by their "task closeness" (Zhang et al., 1999). Having multiple cranes on site can create multiple feasible task areas that can overlap. Overlapping task areas create task groups, so when the areas created by the task groups do not overlap then additional cranes are needed to provide access to the tasks. The authors also accounted for the loading and unloading delays that could occur during construction with random variables and normal distributions, and applied their methodology to a theoretical case study with acceptable results. However, the model presented by the authors does not completely replicate the experience of site managers to allow them to use their approach as a standalone procedure.

Huang, Wong, and Tam (2011) formulated the tower crane allocation problem as a quadratic assignment problem (QAP) and used mixed-integer linear programming (MILP) as their means of optimization. The problem with assigning it as a QAP is the potential high number of local optimum solutions, so the search space must be investigated somewhat extensively to find the global optimum solution. Figure 12 illustrates this issue with the grey area signifying the search space. Further, due to this reason an approach or algorithm attempting to find the global best solutions might take extensive amounts of time before it reaches it. The authors also considered the concept of homogeneous and non-homogeneous supply locations. A homogeneous supply location is a supply point that only carries a specific type of material while a non-homogeneous can carry multiple types of materials. Theoretically, non-homogeneous supply points could influence the transportation time of the crane since it can allow the crane to serve multiple demand points from the same supply location, especially if the supply point is near the demands. Their objective was to minimize the total costs of operating the crane and their objective function can be seen on Equation 19, where T is the transportation time between supply and demand facilities (Equation 20), Q is the quantity of material type being transported, and C is the cost per time unit.

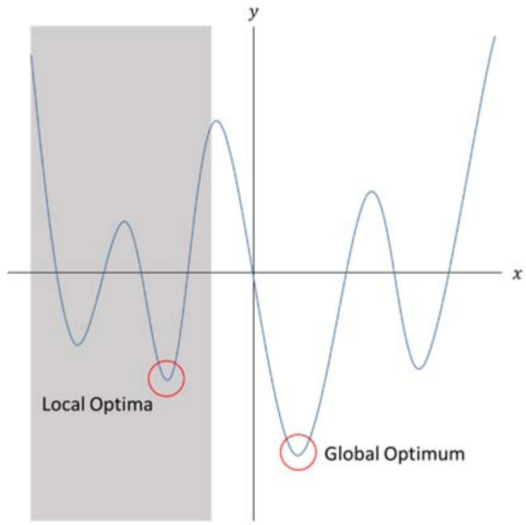


Figure 12. Local Optima vs. Global Optimum

$$TC = \sum \delta TQC \tag{19}$$

$$T_{ij} = \gamma\{Max(T_{hij}, T_{vij}) + \beta * Min(T_{hij}, T_{vij})\} \tag{20}$$

Additionally, the authors considered the difficulties an operator might encounter as it operates the crane with factor γ. This factor affects the time it takes for the crane move from facility to facility, so it is applied to the transportation time equation left by Zhang et al. (1999). The authors applied their methodology to a case study from the literature that utilized genetic algorithms (GA) and proved to perform better. However, some inconsistencies can be found on their work. The authors, on their paper, showcased the values of α and β switched from the original values set by Zhang et al. (1999) and did not provide an explanation for this change. This can result in discrepancies for researchers and scholars that attempt to recreate their work since the authors illustrate results that cannot be obtained using the values on their paper.

Irizarry and Karan (2012) combined the strengths of building information modeling (BIM) and geographic information system (GIS) for the tower crane allocation problem. GIS is known to offer analysis of spatial data while BIM provides superior three-dimensional capabilities. Similar to Zhang et al. (1999), the authors attempted to optimize the location for multiple tower crane on site in terms of cost and based their methodology to check for crane conflicts on their work. However, the authors did not elaborate on the cost functions or objective functions used to achieve such objectives.

Sohn et al. (2014) developed a system that accounted for the optimal selection of tower crane while considering its supporting design. This supporting design encompasses areas such as the crane's foundation design and its lateral support. Their framework is essentially composed of three main modules: 1) selection of a tower crane, 2) design of lateral supports, and 3) crane foundation design (Sohn et al., 2014). Each of the modules analyzes the crane type chosen based on its respective module requirements to then gather an estimated cost based on the chosen crane properties. For example, a crane with a jib configuration of 50 meters can be chosen to then have a lateral wall bracing system placed on a concrete piles foundation. Each of these options will also come with their respective estimated costs. In their paper, some missing wording, such as the number of generated cases, during the explanation of some concepts as well as typos can be found, which might present some problems to the reader attempting to understand their concepts.

To minimize the total travel time of the crane, Zavichi et al. (2014) generated a model that determined the best sequence of service requests by modeling the problem based on the traveling salesman problem (TSP). This modeling of the problem based on TSP assumed the crew areas and material points to be nodes, where the edge distance from the tower crane position to the nodes were taken to represent the cities travelled to in TSP. In addition, the distance traveled, which is usually seen on the edges connecting the nodes, on TSP was instead taken as the total travel time of the hook. The authors used a hypothetical example where the many material and crew nodes were situated around one tower crane, and used their optimization model against commonly used scheduling techniques such as first-in-first-out (FIFO), shortest job first (SJF), and nearest neighbor first (NNF). These scheduling techniques vary in the order in which tasks get addressed. For example, in FIFO the requests that are received first will be fulfilled first in that order (i.e. fast food lines) while in SJF and NNJ the tasks are satisfied based on taking jobs with the shortest travel time or jobs that are nearest to the crane respectively. Formulating the tower crane travel time in similar fashion to past models, Zavichi et al. (2014) achieved the best savings in comparison to the other scheduling techniques. However, the authors only considered one tower crane location in their model which leaves the possibility of other possible locations producing more optimal sequences and travel times than the one showcased.

Moussavi Nadoushani, Hammad, and Akbarnezhad (2016) provided an extensive work that incorporated the influence that the crane's lifting capacity has on the total costs of the crane. Their concepts are based on the premise that higher loads will require types of cranes that impose higher energy consumption rates, maintenance costs, and operating wages (Moussavi Nadoushani et al., 2016). The loads further from the crane's location will require higher loading capacities. Thus, the rental and operating costs are affected by the crane's location. Their objective was to minimize these total costs, considering both rental and operating costs, and their objective function can be seen on Equation 21. This formulation is very similar to the one developed by Huang et al. (2011) with the addition of the rental and operating costs parameters $l_k C_k^r$ and $l_k C_k^o$.

$$Minimize \sum_{k \in K} \sum_{j \in J} \sum_{i \in I} \delta_{ijk} * T_{ijk} * Q_j * (l_k C_k^r + l_k C_k^o) \qquad (21)$$

The authors also constrained the supply points based on the maximum imposed load created. This means that for every tower crane location the supply points would be assigned only if they do not exceed the maximum load constraints set by the demands. Their optimization method was

MILP as well and it provided the authors with the best tower crane location from a set. However, the authors used the incorrect angular time formulation left behind by Zhang et al. (1996) and were not detailed in explaining the quantity of material used for the facilities. In addition, they utilized 968 demand points on their model but lacked this information on their manuscript for space considerations. This will make it difficult for their results to be verified since not all information is provided on their paper.

Artificial Intelligence

The last decade and a half have provided works that utilized artificial intelligence techniques to allocate the tower crane. Some of these include genetic algorithms (GAs), swarm-based intelligence techniques, and hybrid approaches from the two. The next sections in this chapter will detail the numerous contributions to the tower crane allocation problem based on the artificial intelligence method used.

Genetic Algorithms

Genetic algorithms (GAs) are a heuristic computational technique based on the concept of natural selection. This approach creates a population of solutions – termed as chromosomes – and modifies it over time with the goal of attaining the optimal solution. This process begins with the creation of a population of solutions known as chromosomes. The members undergo an evaluation to determine the best fitted members of the population. The members then exchange their genes through cross over – mating – or mutation in hopes of creating higher fitted offspring. If the offspring has a higher merit than the lowest members of the population, then the offspring replaces them and the cycle repeats for generations. In this approach, the important parameters are the population size, cross-over and mutation rates, and the number of generations (Elbeltagi, Hegazy, & Grierson, 2005).

The first work that utilized this technique for optimizing tower crane location was developed by Tam, Tong, and Chang (2001). The GA was used for the optimization of the supply locations around the crane as opposed to optimizing the tower crane location. Their model was based on the mathematical equations left behind by Zhang et al. (1999) and they utilized a construction project in Hong Kong to minimize the total costs of the crane. Further, the authors contributed the velocity values from actual site measurements and added the option of multiple material types that can be supplied by the supply points. Nevertheless, the authors missed explaining and illustrating the composition of the chromosomes in their GA model. Furthermore, the authors' description of the GA model lacks clarity as they state that four chromosomes represent the material types and the tower crane. This terminology creates confusion as the chromosomes themselves, in the general sense, contain the string of information in the genes, not the chromosomes as a whole.

Tam and Tong (2003) expanded on the research left by Tam et al. (2001) by combining both GAs and artificial neural networks (ANN). The artificial neural networks were employed for the prediction of the crane's hoisting and return time, and the genetic algorithm was used to optimize the supply and tower crane locations on site. Tam and Tong (2003) used the same case study as Tam et al. (2001) and received successful results that were accepted by site planning engineers.

Alkriz and Mangin (2005) created an optimization model that utilized genetic algorithms to situate tower cranes. Their model accounted for the number of crane cycles needed to construct building zones as well as conflict checks when using multiple tower cranes. These building zones were further divided by the authors into two work categories: vertical and horizontal. The vertical work category could include work items such as column erection or wall construction while horizontal works could be the setting of beams or slabs. In addition, Alkriz and Mangin (2005) based their mathematical formulation on previous works (Zhang et al., 1996; Zhang et al., 1999) and mathematically considered the balance of workloads when utilizing multiple cranes. This was to ensure that all cranes are being efficiently used without one of the cranes being overly selected, which could make other cranes stay idle. The authors also considered the labor costs that associate with the delivery of tasks, such as when the workers aid loading and unloading in deliveries. However, something to note is that, due to their basis on past formulation, Alkriz and Mangin (2005) used the incorrect angular travel time formulation derived by Zhang et al. (1996).

Abdel-Khalek et al. (2013) created a research work that implemented the use of genetic algorithms to optimize the tower crane location. In similar fashion to the work by Alkriz and Mangin (2005), the authors modeled the transportation considering the number of buildings and their respective number of stories on site. As a result, the authors considered the number of times or cycles performed by the crane per story of each building. Additionally, the authors developed a more accurate representation of the vertical travel time of the hook by breaking the component into a vertical travel time when the hook is loaded and another where it is unloaded. This separation represents a more realistic scenario since other models assume a constant vertical velocity regardless of whether the hook is lifting a load or not. Furthermore, their work provided the correct formulation for the angular travel time component, which many other works displayed erroneously. However, some items to note on their work is that information was lacking on some of their presented formulation, such as the radial and angular travel time equations. These equations are incomplete as variables are missing or the entire formulation is omitted, which might create confusion among readers reviewing their work.

Another GA model developed to optimize the tower crane location was developed by Abdelmegid, Shawki, and Abdel-Khalek (2015). The authors' main contributions were improvements to the tower crane model left behind by previous works, which included the consideration of the number of cycles, a more accurate representation of the crane's vertical velocity, and tower crane base constraints to situate it on areas feasible for their base (Abdelmegid et al., 2015). The vertical travel time was split by the authors into a loaded vertical velocity component and an unloaded one. The resulting equations can be seen as:

$$TL_{vij} = \frac{z_{ij}}{V_{vl}} \quad TU_{vij} = \frac{z_{ij}}{V_{vu}}$$

As a result, the updated total vertical time formulation can be seen on Equation 22, where TL_{vij} is the vertical travel time of the loaded hook and TU_{vij} is the unloaded vertical travel time. This was an improvement since previous models were ran under the assumption that the vertical velocity was constant despite the hook lifting loads during the crane cycles.

$$T_{vij} = TL_{vij} + TU_{vij} \tag{22}$$

Although Abdelmegid et al. (2015) provided improvements to the tower crane model, a discrepancy on their work is the lack of information regarding their objective function and set of constraints. The authors claim results but without this information it creates difficulties verifying their work.

Recently Marzouk and Abubakr (2016) developed a framework that incorporated the usage of genetic algorithms and building information modeling (BIM). This framework was developed to assist planners determine the appropriate location for the tower cranes as well as the tower crane type. The tower crane locations were provided from the optimization process of the GA while BIM would be used to visualize and check for possible collisions between the tower cranes and the surrounding area. An actual construction project was used by the authors to employ their approach with results showing a substantial amount of costs savings when comparing their layout to a proposed layout from crane vendors (Marzouk & Abubakr, 2016). However, the authors lacked comparing the performance of their optimization approach – GA – with other powerful means of optimization.

Swarm-Based Intelligence

In nature, there are a number of species that have demonstrated the influence of their collective efforts to achieve a common goal. Some examples include ants working together to provide the necessary resources for survival, bees scouting their surroundings in search of food locations, and zebras traveling and staying in packs to mitigate the changes of getting killed. This "swarm" behavior has influenced the creation of new artificial intelligence techniques that have been recently used to optimize tower crane locations and their surrounding facilities.

Lien and Cheng (2014) developed a hybrid optimization technique from bee algorithm (BA) and particle swarm optimization (PSO). Entitled particle bee algorithm (PBA), the approach is based on the collective swarm intelligence exhibited by bees and birds in nature. The concept behind the BA comes from the natural foraging behavior of honeybees. Bees in the wild send scout bees to search for potential food sources and communicate their findings through a dance. The scout bee can change the pattern of the dance, the duration, and the speed to communicate different aspects about the site. This information is then used to evaluate the sites, and bees will be sent according to the fitness of the sites. With regards to PSO, the approach mimics the manner in which flocks of birds travel and reach destinations. Their communication exchange happens when determining the bird closest to the destination. Once known, the birds fly towards it to repeat the cycle until the destination is reached (Elbeltagi et al., 2005). Although both approaches prove to be high performing, BA does not keep track of past searches, relies on random searches, and PSO has the potential to converge prematurely in highly discrete problems (Lien & Cheng, 2012). Thus, the basis for the development of PBA. The authors used the same case study from Tam et al. (2001) and added rental, set up, and labor costs to the model. The authors, however, were not clear explaining the quantity of material flow values used on their model. Furthermore, Lien and Chen (2014) also switched the values of α and β from their original values set by Zhang et al. (1999) but missed providing an explanation for the change.

Wang et al. (2015) contributed the application of a new swarm-based intelligence approach to the tower crane allocation problem with the usage of BIM. Similar to Marzouk and Abubakr (2016), their developed framework involved the new approach, known as firefly algorithm (FA), to optimize the tower crane location and BIM for data and output visualization (Wang et al., 2015). The algorithm is based on the behavior exhibited by fireflies when communicating with each other. These insects rely on their luminosity and light patterns to search for food and mates (Gandomi, Yang, & Alavi, 2011). Fireflies with greater luminosity will attract those with dimmer lights, so distance will also affect the attractiveness of the fireflies. In this case, the quality of the objective function can be represented by the brightness of the firefly solution – the better the solution the brighter the firefly (Gandomi et al., 2011; Wang et al., 2015). The authors used an actual construction project to test their methodology and the resulting layout was granted the honor of being selected as the final scheme for tendering purposes (Wang et al., 2015).

Harmony Search and Simulated Annealing

When it comes to the utilization of distinct optimization techniques from the ones previously discussed, Lee et al. (2015) developed a unique tower crane allocation model that focused solely on the luffing boom tower crane type. Their model presented a new formulation to account for the different movements exhibited by the luffing boom. For example, Lee et al. (2015) added the consideration of the luffing velocity (the velocity of the boom as it lifts up) and, consequently, the total time spent on luffing operations. Additionally, the authors used harmony search (HS) as their means of optimization. This technique is based on the continual effort from players, playing their instruments, to change their instrument pitch to achieve a greater harmony (Geem, Kim, & Loganathan, 2001; Lee et al., 2015). Utilizing an actual construction project, the authors were able to achieve a better location from their HS model in comparison to the optimal solution from preliminary research. However, Lee et al. (2015) also utilized the incorrect formulation that accounts for the angular travel time, which could potentially make their optimal solution not the most optimal crane location.

Monghasemi et al. (2016) created an additional model that incorporated the HS algorithm into a more comprehensive framework to minimize the pending times of the crane's service request. The authors note that the total travel time constitutes an objective that, while optimal, might not be as practical if there is variation occurring on the waiting times of request (Monghasemi et al., 2016). Thus, they developed a framework composed of game theory, improved harmony search (HIS), and a least deviation method (LDM) with a power index (PI) approach to fully minimize the deviation of idle times as well as finding an optimal distribution of request priority such that the deviation is effectively distributed. Utilizing a similar travel time formulation scheme as Zavichi et al. (2014), as well as their numerical example, Monghasemi et al. (2016) effectively distributed the pending times of service requests. Nonetheless, much like Zavichi et al. (2014), the limitation in their work is the consideration of only one tower crane location as opposed to many other potential locations that could contribute to a more efficient distribution of waiting times and less hook travel times.

Tubaileh (2016) presented a work that focused on addressing the concept of constant velocities used on past works. This assumption of velocities occurring at a constant rate has been utilized on past models since they were introduced by Tam et al. (2001). In actuality, however, the assumption of constant velocities does not accurately represent the real-world conditions on the field. Thus, Tubaileh (2016) presented kinematic and dynamic models and optimized the tower crane location using simulated annealing (SA). This technique was built upon the observed behavior of annealing that happens in metals. Their case study was taken from the work by Huang et al. (2011) and their results showed a difference in performance that was likely caused by the more accurate velocity representation on his model.

CHAPTER III

ACO AND TOWER CRANE ALLOCATION

Introduction

Tower crane is one of the most elemental machines needed to accomplish large construction projects. The tower crane's ability to lift heavy material loads set it apart from the rest of the construction equipment. In addition, tower cranes also offer load-carrying capabilities at much higher elevations and save space by meeting material demand requirements from one location. However, these cranes come with high costs of assembly, rent, and operation. For these reasons, it is critical to place these cranes in locations that maximize their efficiency and minimize the incurred costs. Many research works have been published that introduced approaches and techniques for the optimization of tower crane location (Abdel-Khalel, Shawki, & Adel, 2013; Abdelmegid, Shawki, & Abdel-Khalek, 2015; Alkriz & Mangin, 2005; Choi & Harris, 1991; Furusaka & Gray, 1984; Huang, Wong, & Tam, 2011; Izarry & Karan, 2012; Lee, Lim, Cho, & Kang, 2015; Lien & Cheng, 2014; Marzouk & Abubakr, 2016; Moussavi Nadoushani, Hammad, & Akbarnezhad, 2016; Rodriguez-Ramos & Francis, 1983; Tam, Tong, & Chan, 2001; Tam & Tong, 2003; Tubaileh, 2016; Wang et al., 2015; Zhang, Harris, & Olomolaiye, 1996; Zhang, Harris, Olomolaiye, & Holt, 1999). However, few of them, such as Trevino and Abdel-Raheem (2017), have adopted the use of ant colony optimization (ACO) to the tower crane allocation problem. Further, many of the models in the literature contain errors and discrepancies that create potential challenges to future researchers attempting to develop tower crane allocation models. As such, the reconstruction of many of the models found in the literature is necessary to prevent anyone from incorporating the flaws of past models and obtaining incorrect results. Further, the inclusion of ACO could serve as potential benchmark for researchers to compare their methodologies and optimization techniques due to its rare use.

Objectives

Due to the findings of Trevino and Abdel-Raheem (2017a), the objectives of this research include the reconstruction of previous known models (Choi & Harris, 1991; Huang et al., 2011; Lien & Cheng, 2014; Moussavi Nadoushani et al., 2016; Tam et al., 2001; Zhang et al., 1996) and the application of ACO to the reconstructed models.

Methodology

The original intent of this research was the development of a comprehensive tower crane allocation model and incorporation of Building Information Modelling (BIM) for the use of managers and construction planners in the industry. However, after conducting careful examinations of the literature, it became apparent that many of the tower crane allocation models contained critical flaws and limitations (Alkriz & Mangin, 2005; Huang et al., 2011; Lee et al., 2015; Lien & Cheng, 2014; Moussavi Nadoushani et al., 2016; Tam et al., 2001; Tam & Tong, 2003; Wang et al., 2015; Zhang et al., 1996; Zhang et al., 1999) that hinder their use by industry personnel and researchers. Thus, it became a responsibility to rebuild these models and point out their limiting factors and weaknesses to prevent future researchers from using flawed tower crane allocation models.

As such, the methodology used to achieve the aforementioned objectives begins with the careful examination of each tower crane allocation model found in the literature. Investigation of models and all formulation was performed, and models were rebuilt to verify their results and conclusions. Any discrepancies, errors, or issues were documented, and further research was made to determine the sources of error. Models were reconstructed to include fixes to these sources of error. ACO was then implemented as the means of optimization in the reconstructed models, results were gathered, and comparisons were made.

Previous Models

Optimizing the location of the tower crane in construction sites has proved to be an interesting problem, and many models were developed to solve this allocation problem. Rodriguez-Ramos and Francis (1983) were the first to contribute a mathematical model that accounted for the crane's radial and angular movements. Their model employed a graphical approach and was able to determine the best tower crane location from a set based on minimal hook travel time. Furusaka and Gray (1984) developed a crane selection model with the capacity of selecting the appropriate crane type and its location on site. Choi and Harris (1991) created a model based on the mathematical formulations from Rodriguez-Ramos and Francis (1983) and included the frequent movement performed by the crane between its surrounding facilities. Zhang et al. (1996) provided a very influential work that simulated the crane's sequence of deliveries using Monte Carlo simulation. Their work also updated the previous mathematical formulations used to estimate the hook travel time. Some additional updates, in the form of parameters, were used to describe how consecutive or simultaneous the hook movements are along the horizontal plane, which results in a more accurate representation of hook movement in site. Zhang et al. (1999) further improved on their previous work by considering multiple tower cranes on site and the vertical component of hook travel time. In addition, their model considered ways to reduce potential crane conflicts, as well as statistical distributions to simulate the loading and unloading times. Tam et al. (2001) were the first to develop a genetic algorithm (GA) model to optimize supply locations around the tower crane and incorporated actual velocity values from site observations. Tam and Tong (2003) expanded on the work of Tam et al. (2001) by using artificial neural networks (ANN) in combination with GA. Their ANN model granted a statistical figure for the crane's hoisting time, while the GA was employed to optimize the facility locations. Alkriz and Mangin (2005) provided another GA model that accounted for multiple tower cranes, considered checks for potential collisions, and incorporated building zones for the use of crane cycles. Huang et al. (2011) established a mixed integer linear programming (MILP) model for the optimization of the crane and supply facilities. MILP is a technique known to find global optimum solutions, and it demonstrated higher performance than GA in determining the best locations of the facilities. Irizarry and Karan (2012) created a framework that utilized BIM in conjunction with Geographic Information System (GIS) to situate tower cranes. Abdel-Khalel et al. (2013) presented a supplementary GA optimization model that considered updates to the hoisting hook travel times. Lien and Cheng (2014) developed a hybrid approach called Particle Bee Algorithm (PBA) used to optimize the quantity of material needed between supply and demand pairs. Another model that focused on selecting the most optimal tower crane was created by Sohn et al. (2014), in which foundation design and lateral support were the characteristics accounted for by the model. Zavichi, Madani, Xanthopoulos, and Oloufa (2014) developed an approach used to determine the optimal sequence of service requests based on the Traveling Salesman Problem (TSP). Abdelmegid et al. (2015) provided an additional GA model used to optimize the tower crane location. Their model offered improvements and updates to the tower crane model that included a more accurate representation for the number of cycles, hook vertical travel time, and tower crane base. Lee et al. (2015) created an allocation model for luffing boom tower cranes that considered the different lifting movements performed by these cranes. Wang et al. (2015) published a framework that incorporated Firefly Algorithm (FA) to optimize the position of the tower crane and supply facilities, and used BIM to visualize the layout. Marzouk and Abubakr (2016) contributed an additional comprehensive framework that used GA and BIM for selecting the appropriate tower crane and its location. Monghasemi, Nikoo, and Adamowski (2016) focused on the time spent between requests and granted a model that minimized the pending times of the crane's service request. Tubaileh (2016) reconstructed the manner in which past models accounted for the crane's hoisting operations by means of kinematic and dynamic models. The tower crane model by Moussavi Nadoushani et al. (2016) considered the effects load capacities impose on the operational and rental costs of the crane. Trevino and Abdel-Raheem (2017a) introduced an ACO model to solve the single tower crane allocation problem, and it proved to perform as high as MILP when finding the best tower crane location.

Limitations and Shortcomings of Previous Models

Despite the valuable contributions made to the tower crane allocation problem by the aforementioned researchers, there are various works that exhibit some limitations, issues, and discrepancies in their models. Rodriguez-Ramos and Francis (1983) applied their approach on a rather simple numerical example and, much like Furusaka and Gray (1984), Choi and Harris (1991), and Zhang et al. (1996), their model did not consider the hoisting movement of the crane. Furusaka and Gray (1984) considered the possible use of multiple tower cranes but did not account for the possible collisions that might occur between the cranes. Choi and Harris (1991) determined the best tower crane location from a set of only four predetermined positions, which leaves out other potential locations that might be more optimal. A critical shortcoming in the work of Zhang et al. (1996) is the incorrect formulation that considers the angular travel time of the hook (qtd. in Treviño & Abdel-Raheem, 2017a). This mistake could lead to overestimations or underestimations of the angular travel time and has been carried on throughout the literature in many other works (Alkriz & Mangin, 2005; Huang et al., 2011; Lee et al., 2015; Lien & Cheng, 2014; Moussavi Nadoushani et al., 2016; Tam & Tong, 2003; Tam et al., 2001; Want et al., 2015; Zhang et al., 1999). Zhang et al. (1996) also mentioned using an effective algorithm for the determination of feasible area but do not further explain nor illustrate the algorithm in their manuscript. The models by Huang et al. (2011), Lien and Cheng (2014), Tam et al., (2001), and Tubaileh (2016) used switched parameter values of α and β from the original set described by Zhang et al. (1999) without explanation. In addition, some of the mathematical formulas in the model by Lien and Cheng (2014) contain logic errors and the authors do not go into much detail explaining their reasoning behind their formulations. Irizarry and Karan (2012) failed to provide cost and objective functions in their manuscript. Abdelmegid et al. (2015) did not clearly illustrate the objective function and how their improvements to previous tower crane models are accounted by it. Moussavi Nadoushani et al. (2016) provided the structure of their mathematical model but did not clearly discuss the needed quantities of material transported.

ACO Application

Ant colony optimization (ACO) is an artificial intelligence approach developed in 1992 by Dorigo based on the natural tendencies of ants as they search for food sources. Ants are mostly blind creatures that depend on a chemical substance known as pheromone to communicate. The ants release this substance as they travel for food in random directions, creating pheromone trails that aid the ants return to the nest. The ant with the shortest route to the food source returns to the nest and back to the food the fastest, which results in more pheromone deposited by the ant. This reinforcement of pheromone on the trail creates a stronger signal that, eventually, gets perceived by other ants that begin to use it. The end result is the ant population gradually converging towards the shortest path between the food and the nest.

In the theoretical application, Abdel-Raheem, Georgy, and Ibrahim (2013) have summarized the ACO approach into six principal steps:

1) Generating trial solutions. In this initial step, an ant population of M ants is created. As seen in Figure 13a., each ant k contains a number of variables V that represent the points visited by the ant, and each variable has a possible option j randomly selected by the ant. Further, each of the variable options has a pheromone value τ associated with it. In tower crane allocation problems, it is common for the ant to have facility coordinates in their variables, such as in Figure 13b., or facility indices that represent the order of facilities that the crane must service, as shown in Figure 13c.

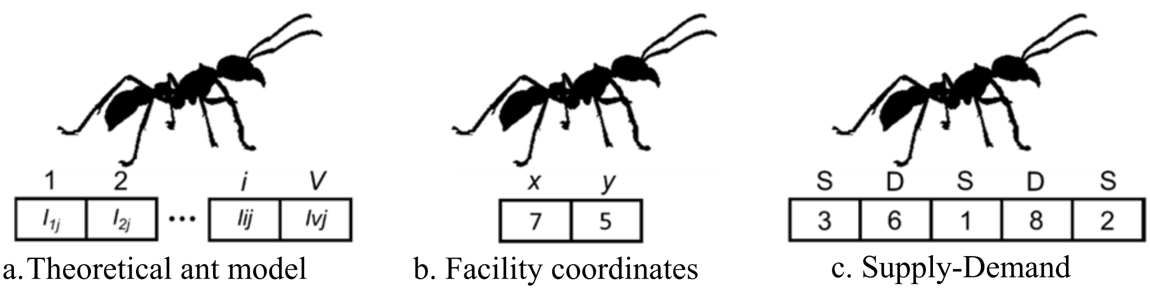


Figure 13. Ant Model and Variable Options for Tower Crane Allocation Problem

2) Heuristic Information. This piece of information is known about the problem's optimal solution beforehand and serves as guidance to the ant as it searches the solution space. This gives the ant clues as to options that are thought to be part of the optimal solution. In tower crane allocation problems, this information can be represented by the total distance between the tower crane and its surrounding facilities.

3) Evaluation. Each ant is evaluated with respect to an objective function. Some common objectives for tower crane allocation problems include the minimization of total hook travel time and minimization of total costs.

4) Pheromone update. Each of the ant updates its pheromone values in such a way to reinforce better routes. This update is done in accordance to Equation 23, where $\tau_{ij}(t)$ is the pheromone concentration associated with option j of variable i at iteration t, ρ is the pheromone evaporation rate, $\tau_{ij}(t-1)$ is the pheromone concentration at the previous iteration, and $\Delta\tau_{ij}$ is the change in pheromone concentration. The change in pheromone is further done using Equation 24, where R is the pheromone reward factor, $f(\varphi)_k$ is the objective function value of ant k, and M is the number of ants.

$$\tau_{ij}(t) = \rho * \tau_{ij}(t-1) + \Delta\tau_{ij} \tag{23}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{M} \begin{cases} \frac{R}{f(\varphi)_k} \; if\ option\ l_{ij}\ is\ selected \\ 0\ otherwise \end{cases} \tag{24}$$

5) Probability Update. The probability of an ant selecting an option as it travels its path is determined using Equation 25, where $P_{ij}(k,t)$ is the probability of ant k selecting option j for decision point i at iteration t, $\tau_{ij}(t)$ is the pheromone concentration associated with option j at decision point i, η_{ij} is the heuristic information that favors certain options depending on the problem, and α and β are exponent factors that distribute the weight between the pheromone concentration and heuristic value (Elbeltagi et al., 2005). These exponents provide the user the freedom to choose whether randomness or heuristic information controls as ants search for the optimal solution.

$$P_{ij}(k,t) = \frac{\tau_{ij}(t)^{\alpha} * \eta_{ij}{}^{\beta}}{\sum \tau_{ij}(t)^{\alpha} * \eta_{ij}{}^{\beta}} \tag{25}$$

6) Termination. In this last step, a stopping criterion is determined. This criterion could be after the execution of a number of iterations or after a specified time.

The next sections will discuss each of the models that were reconstructed and used for the application of ACO. Any discrepancies or errors on previous models will be highlighted and discussed and the modifications made to the ACO model will be explained.

Choi and Harris (1991)

The first model that was reconstructed for the implementation of ACO was based on the original work done by Choi and Harris (1991). As brief background, the authors, in their model, considered the radial travel time of the trolley, the angular travel time of the crane as it rotates, and how frequently the crane travels to each of its surrounding facilities. The radial and angular travel times are based on Cartesian coordinate positions, and the movement frequency is described by the authors as a percentage of total movement called Interfacility Weighting (ITFW) (Choi & Harris, 1991). Equations 26 and 27 were used by the authors to determine the radial and angular times, respectively, and Figure 14 illustrates the equation parameters in a graphical format. The ITFW percentage must be determined for each supply-demand pair, and it is done by dividing the total number of times the crane moved from a specific supply-demand pair by the total overall movement.

$$Radial\ Travel\ Time = \frac{|r_n - r_m|}{CRV} \tag{26}$$

$$Angular\ Travel\ Time = \frac{A(\theta_n, \theta_m)}{CAV} \tag{27}$$

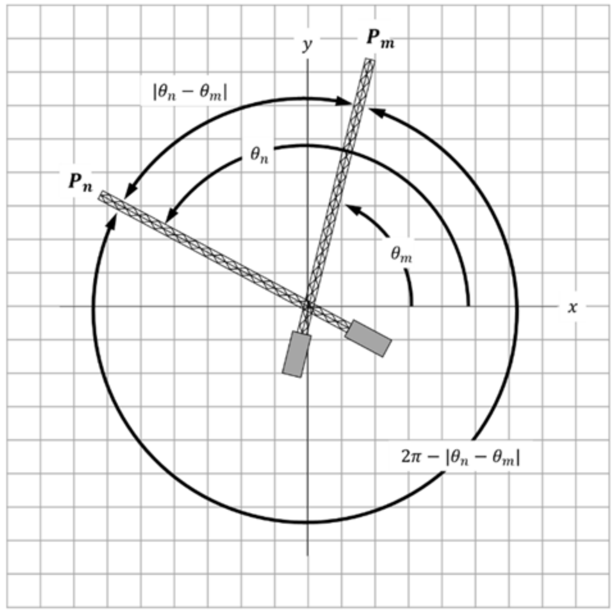


Figure 14. Angular Crane Movements (Choi & Harris, 1991)

Using the aforementioned concepts, the author's travel time equation between two facilities can be seen in Equation 28, where $ITFW_{n\leftrightarrow m}$ is the Interfacility Weighting of facilities n and m, $A(\theta_n, \theta_m)$ is the minimum angle between facilities n and m, $|r_n - r_m|$ is the distance traveled by the trolley as it moves from facility n to m, and CAV and CRV are the angular and radial velocities, respectively. The "2" was placed by the authors to describe a return movement for reloading (Choi & Harris, 1991). In order to determine the total travel time imposed by a crane location, Equation 28 will have to be applied for all possible facilities. It is worth noting that the authors expressed the resulting transportation costs in terms of crane operating time (Choi & Harris, 1991). This means that the results from Equation 28, although given in time, are considered in costs as well.

$$2\left[ITFW_{n\leftrightarrow m} * MAX\left(\frac{A(\theta_n,\theta_m)}{CAV}, \frac{|r_n-r_m|}{CRV}\right)\right] \tag{28}$$

The numerical example that will be used will be the same as the authors'. This example consists of a construction project in Hong Kong and the site layout, with the facilities in place, can be seen in Figure 15.

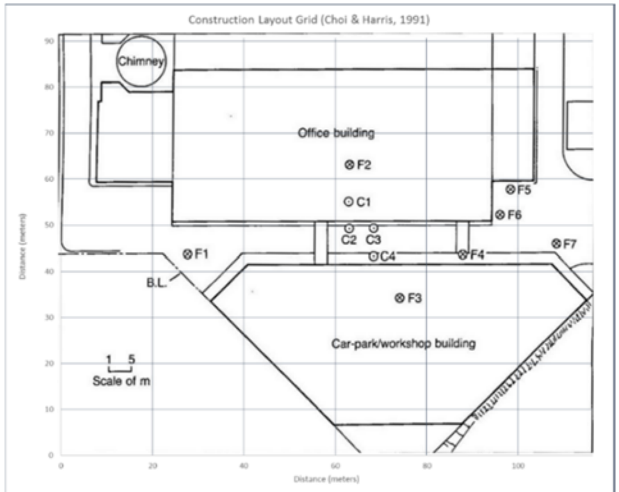


Figure 15. Project Site Plan (Choi & Harris, 1991)

To reiterate, the limiting factor in their work is the lack of consideration of other nearby areas. Therefore, the primary reconstruction in this model is the expansion of the original scope to include other tower crane locations through an exhaustive search. This search will scout other possible locations nearby that still permit the crane to reach all the facilities with its boom. Figure 16 shows the feasible tower crane locations of this search with respect to the surrounding facilities.

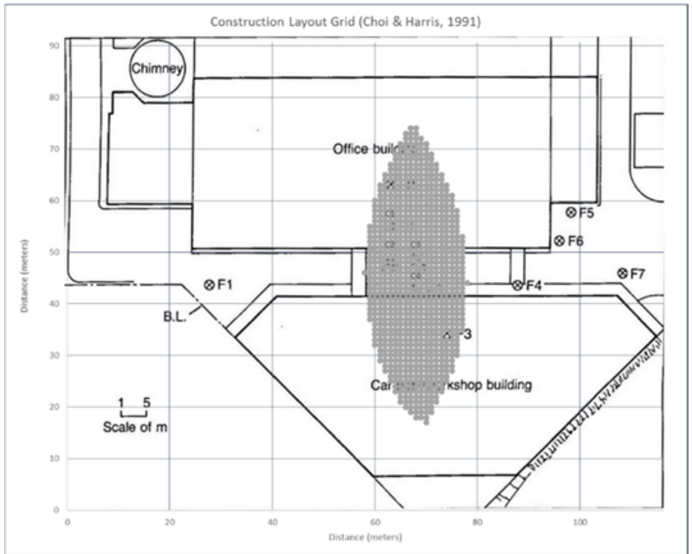


Figure 16. Site Plan With Feasible Tower Crane Locations (Choi & Harris, 1991)

The ant in the ACO model contains two variables that represent the tower crane location in Cartesian coordinates, as seen in Figure 17, and each ant is restricted to select locations based on the boom constraint. Each ant is evaluated based on the objective function, Equation 28, and the heuristic information used for this problem was based on a distance relationship between the crane and its surrounding facilities. To further elaborate on the determination of the heuristic information, the angular and radial distances for all facilities were gathered and summed together. After, a sufficiently large number – "1000" in this case – was taken and divided by the total summation of the terms. This was done so that tower crane locations further away from the demand facilities have less chance of being selected by the ants.

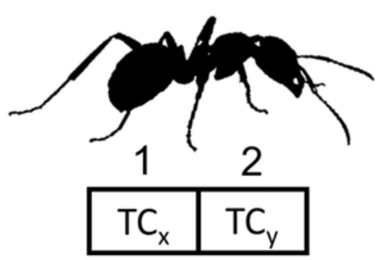


Figure 17. Ant Model for Choi & Harris (1991) and Zhang et al. (1996)

Results and Discussions

The reconstructed ACO model was coded in VBA environment and took roughly two minutes on a machine with 8 GB of RAM. The ant parameters that provided the three best tower crane locations were a pheromone reward, R, of 0.5, pheromone evaporation, ρ, of 0.4, 10 iterations, t, 25 ants per iteration, α of 0.3, and β of 1.5. The three best ant solutions can be seen in Table 1, and the best tower crane location with respect to the feasible solutions can be seen highlighted in Figure 18.

Table 1. Best Ant Solutions For Choi And Harris (1991)

X	Y	Total Transportation Time (min.)
70	17	100.7635
69	18	101.9641
71	19	104.3056
Run time:00:02:07		

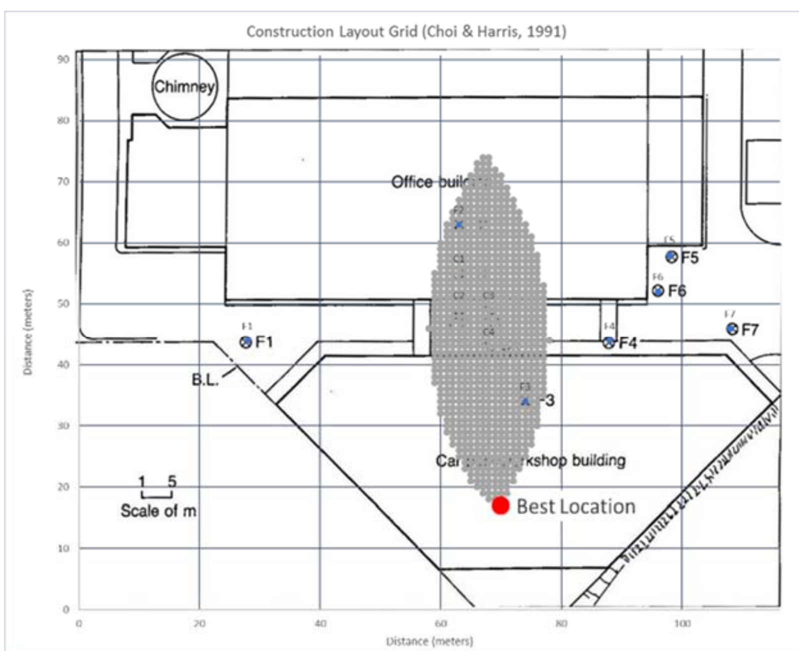


Figure 18. Choi And Harris (1991) Site Plan With Feasible And Best Solution

The ACO model provided a better tower crane location that significantly improved over the one from Choi and Harris (1991). In this case, the best location from the ACO model reduced the amount of angular movement necessary for the crane to reach the facilities, which positively affected the overall travel time. This indicates that the output is more sensitive to changes in angular movement than those performed radially.

Zhang et al. (1996)

The second reconstructed model originated from the work of Zhang et al. (1996). One of the main contributions from the authors was the utilization of Monte Carlo simulation to mimic the crane as it performs its deliveries in sequences. In addition, the authors provided an updated mathematical model for the calculation of the crane hook travel time. The formulations in their model are based on a Cartesian coordinate system and can be seen in Equations 29 through 34, where ρ_i is the linear distance between demand i and the tower crane, ρ_j is the distance between supply j and the tower crane, l_{ij} is the distance between demand i and supply j, T_a is the travel time of the hook radially along the jib, T_ω is the travel time of the hook as the crane rotates, and TM_{ij} is the total travel time of the hook moving from demand i to supply j. When calculating the total travel time of the hook, the authors used factor α to consider the possible movement coordination that could occur in the horizontal plane. This means that, as the crane moves from one facility to the next, the trolley could move radially as the crane moves angularly. As a result, the radial and tangential (angular) movements could happen consecutively or simultaneously, and α can be set between “0” (fully simultaneous) or “1” (fully consecutive) to describe this movement coordination. Zhang et al. (1996) noted that Kogan (1976) found experienced operators perform simultaneous operations during 76% of the total cycle duration, which led to the α value of 0.25 to be expressed in their manuscript.

$$\rho_i = \sqrt{(XD_i - x)^2 + (YD_i - y)^2} \tag{29}$$

$$\rho_j = \sqrt{(XS_j - x)^2 + (YS_j - y)^2} \tag{30}$$

$$l_{ij} = \sqrt{(XD_i - XS_j)^2 + (YD_i - YS_j)^2} \tag{31}$$

$$T_a = \frac{|\rho_i - \rho_j|}{V_a} \tag{32}$$

$$T_\omega = \frac{1}{\omega} * arccos\left(\frac{{l_{ij}}^2 - ({\rho_i}^2 + {\rho_j}^2)}{2 * \rho_i * \rho_j}\right) \tag{33}$$

$$TM_{ij} = Max(T_a, T_\omega) + \alpha * Min(T_a, T_\omega) \tag{34}$$

It is very important to note that Equation 33 contains an error. This equation is based on the concept of the Cosine Law to determine the minimal angle between the crane and two facilities (previously shown in Figure 14 for this model). However, the manner in which it was displayed by Zhang et al. (1996) does not consider this concept correctly. To illustrate this, a hypothetical triangle can be seen in Figure 19, where $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$ represent the sides of the triangle, respectively, $\boldsymbol{S_j}$, $\boldsymbol{D_i}$, and $\boldsymbol{Cr}$ are the supply, demand, and crane points, respectively, and $\boldsymbol{\theta}$ is the angle created by the boom as it would travel from supply to demand or vice versa.

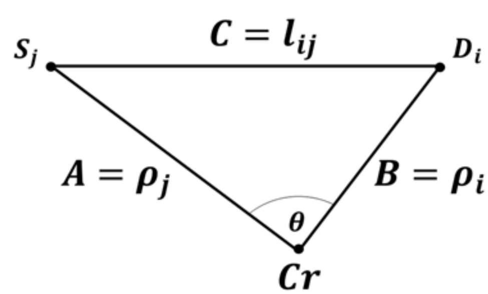


Figure 19. Hypothetical Facility Locations and Distances

Using the cosine law and algebraic operations, the resulting formulation needed to determine $\boldsymbol{\theta}$ will be:

$$\boldsymbol{\theta = arccos\left(\frac{{\rho_j}^2 + {\rho_i}^2 - {l_{ij}}^2}{2 * \rho_j * \rho_i}\right)}$$

Using these terms in place of the ones seen in Equation 33 will result in Equation 35. As shown, this modified formulation switches the terms in the numerator, which can either overestimate or underestimate the total travel time of the hook. Therefore, the ACO model will incorporate this modified equation, as well as the previous equations and parameters, for the determination of hook travel time.

$$T_\omega = \frac{1}{\omega} * arccos\left(\frac{{\rho_i}^2+{\rho_j}^2-{l_{ij}}^2}{2*\rho_i*\rho_j}\right) \quad (35)$$

In their work, Zhang et al. (1996) used the same case study and facility information from Choi and Harris (1991). This case study will be used in the reconstructed model as well. As previously stated, Zhang et al. (1996) mentioned using an effective algorithm to determine the feasible area but did not elaborate much on this approach. Because the feasible area will help in decreasing the calculation time, an algorithm was employed to determine this feasible area. The site plan with the feasible area can be seen in Figure 20.

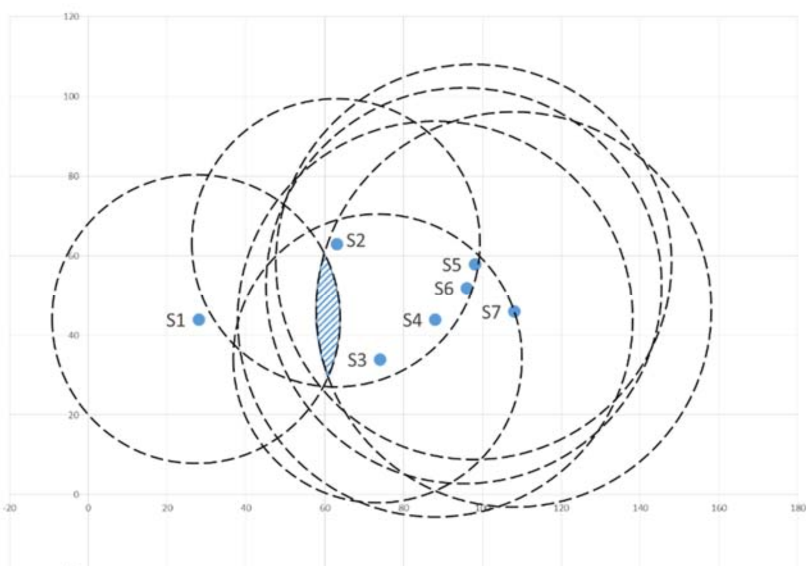


Figure 20. Tower Crane Location Feasible Area (Zhang et al., 1996)

In a manner similar to the previous reconstructed model, the heuristic information for this work was determined by taking a sufficiently large number – “100” – and dividing it by the total linear distance between the selected tower crane location and all demand points. The ant was also modeled with two variables containing the coordinates of the selected tower crane location as seen in Figure 17. After the ant selects its variables, the average transportation time of a request can be approximated using a calculation matrix. An example can be seen in Table 2, where an ant's chosen crane location of (61,48) provided an average time of 1.21 minutes spent per request. These calculations can serve as approximate estimations to verify the results from the model of Zhang et al. (1996).

Table 2. Hook Travel Time Matrix With Average Time

Transport Time, Tij							
Tij	D1	D2	D3	D4	D5	D6	D7
S1	0	1.823972	2.198551	2.873891	2.998253	3.134761	2.978441
S2	1.823972	0	2.260663	1.585323	1.174281	1.324453	1.480772
S3	2.198551	2.260663	0	0.67534	1.086382	0.93621	0.931252
S4	2.873891	1.585323	0.67534	0	0.411042	0.264438	0.658262
S5	2.998253	1.174281	1.086382	0.411042	0	0.150172	0.306491
S6	3.134761	1.324453	0.93621	0.264438	0.150172	0	0.393823
S7	2.978441	1.480772	0.931252	0.658262	0.306491	0.393823	0
						AVG	1.210072

Verification of Results

Calculation matrices were initially made to verify the results of the original model before reconstructing it. The resulting output from these initial calculations demonstrated the faults from using the author's angular travel time formulation. As an example, Table 3 shows an example matrix for tower crane position (61,48) using the original angular travel time formulation. Since the facilities act as both supply and demands points (i.e. both demands and supplies have the same coordinates), the intersecting values should be "0" and not "3.14". No angular movement would be required to be performed, thus the resulting angular travel time should be zero.

Table 3. Example Of Angular Travel Time Calculations Using Original Equation

Angular Travel Time, Tω (min)							
	D1	D2	D3	D4	D5	D6	D7
S1	3.141593	1.317621	0.943042	0.267702	0.14334	0.006832	0.163151
S2	1.317621	3.141593	0.88093	1.55627	1.967312	1.81714	1.66082
S3	0.943042	0.88093	3.141593	2.466253	2.055211	2.205382	2.361702
S4	0.267702	1.55627	2.466253	3.141593	2.730551	2.880722	3.037042
S5	0.14334	1.967312	2.055211	2.730551	3.141593	2.991421	2.835101
S6	0.006832	1.81714	2.205382	2.880722	2.991421	3.141593	2.985273
S7	0.163151	1.66082	2.361702	3.037042	2.835101	2.985273	3.141593

Thus, the calculations were redone with the appropriate angular travel time formulation. With no batch request and an α value of "0", the best location provided by the authors was (60, 38) with an average transportation time of 1.079 minutes per request. Using the modified formulation, the average transportation time for the same tower crane location resulted in 1.106. This discrepancy could be due to the simulation nature of the model used by the authors. However, the best tower crane locations were determined for multiple objectives using Excel's

Solver in an attempt to determine this discrepancy. The results are shown in Table 4, where minimizing the total angular time provided the least average transportation time.

Table 4. Average Transportation Time Results Based On Different Objectives

	Results						Authors' Results (Zhang et al., 1996)					
Objective	α	Radial Velocity (m/min)	Angular Velocity (rad/min)	x	y	Avg. Transportation Time	α	Radial Velocity (m/min)	Angular Velocity (rad/min)	x	y	Avg. Transportation Time
Minimization of total distance between tower crane and all facilities	0	30	1	64.22	47.55	1.261	0	30	1	60	38	1.079
Minimization of Avg. Transportation Time	0	30	1	60.26	60.86	1.076	0	30	1	60	38	1.079
Minimization of Total Radial Time	0	30	1	63.85	46.74	1.250	0	30	1	60	38	1.079
Minimization of Total Angular Time	0	30	1	61.06	28.77	0.955	0	30	1	60	38	1.079

Results and Discussions

Using a pheromone reward of 1, pheromone evaporation of 0.3, 10 iterations, 10 ants, and α and β values of 0.25 and 0.5, respectively, the ACO model achieved the results shown in Table 5. The best ants provided a better average transportation time than the authors with a relatively short time run.

Table 5. Best Ant Solutions For Zhang et al. (1996) ACO Model

X	Y	AVG Transportation Time (min.)
61	30	0.977095613
61	30	0.977095613
61	31	0.995087775
60	33	1.026701063

60	33	1.026701063
Run time:00:00:25		

Tam et al. (2001)

The third reconstructed model in this section was based on the work of Tam et al. (2001). Their model incorporated the usage of GA to find the best tower crane and supply locations that could deliver numerous material types to the demand points. To benchmark the performance of the ACO model against their GA model, the hypothetical example from Tam et al. (2001) will be used. This example represents a harmony housing structure project with nine demand and supply locations and 12 allowable tower crane locations. This project layout can be observed in Figure 21.

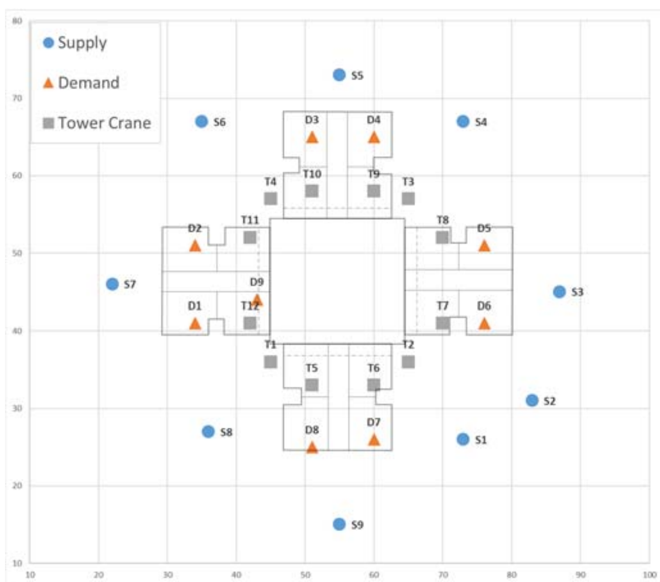


Figure 21. Project Site Plan With Facility Locations (Tam et al., 2001)

Each supply point is allowed to carry one of three different material types: A1, A2, or A3. This means that each material type will have their respective supply points that can supply said type. Material A1 can be provided by supplies one through six, A2 by supplies one through four, and A3 by supplies five through nine. All demand points are assumed to be in need of all three material types. Thus, the objective is to determine which tower crane location and supply points can supply all demand facilities and incur the least costs. Their objective function can be seen in Equation 36, where N is binary variable used for the determination of tower crane position, T_{jk} is the transportation time of the hook between supply j and demand k, Q_{jk} is the quantity of material flow between supply j and demand k, and C_{jk} is the crane cost per minute. Q_{jk} for material types A1, A2, and A3 will be taken as 10, 20, and 30, respectively, and C_{jk} as 1.92.

$$TC = min\{N * [\sum_{j=1}^{n} \sum_{k=1}^{n} T_{jk} Q_{jk} C_{jk}]\} \tag{36}$$

$$TC = min\{N * [\sum_{j=1}^{n} \sum_{k=1}^{m} T_{jk} Q_{jk} C_{jk}]\} \tag{37}$$

It is worth noting that the authors' objective function calls out the same index for both upper boundary terms of the summations ("n"), but this cannot be so. Therefore, the reconstructed model will incorporate Equation 37, which was modified to address this mistake.

An additional piece of information incorporated by Tam et al. (2001) in their model was the vertical travel time of the hook. This consideration will be included in the reconstructed model and the formulation can be seen in Equation 38, where ΔZ is the change in height between supply j and demand k and V_v is the vertical or hoisting velocity of the crane. Further visual representation of the change in hook elevation between two facilities can be observed in Figure 22.

$$T_v = \frac{\Delta Z}{V_v} = \frac{Z_j - Z_k}{V_v} \tag{38}$$

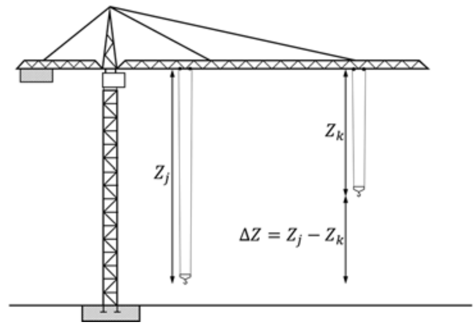


Figure 22. Vertical Hook Travel Time (Tam et al., 2001)

A small discrepancy found in their work are the values of the α and β parameters in comparison to the originals provided by Zhang et al. (1999). The authors appeared to have switched them and provide no explanation for this change, which could cause confusion among readers investigating their work.

In the proposed ACO model, the ant is composed of three variables. Each variable represents a material type, and the ant can select between the available supply points that carry the required material type. However, the ant will be constrained from selecting duplicate supply points for different material types. Figure 23a illustrates the ant model for this problem.

In addition to the ant model, and important consideration needed to solve the problem with ACO is to account for each of the 12 tower crane locations as a different nest. Each nest will then have their best ant solutions, which will allow the global best solution to be determined.

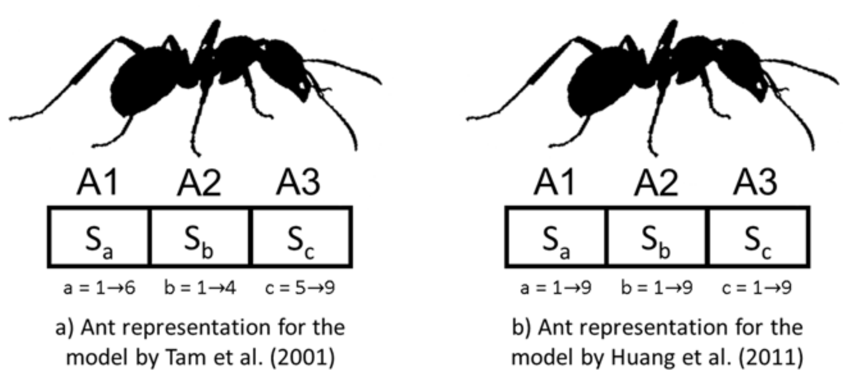


Figure 23. Ant Models For Tam et al. (2001) And Huang et al. (2011)

Finally, the heuristic information for this model will equate the inverse of the total distance between the tower crane and supply facilities. This inverse function will output greater values for tower crane positions that are closer to its supply facilities.

Verification of Results

In a similar manner as before, calculations were first conducted to verify the results provided by the authors. Since their GA model outlined tower crane location two as the best position, spreadsheets were used to determine the total costs for that location. The results from these calculations, considering the incorrect formulation and alpha and beta parameters values as 1 and 0.25, respectively, are shown in Table 6. The total costs of using tower crane position two with supplies three, two, and nine, supplying all demands, is equal to $402.41. In comparison, the authors' best objective function value was $241. The discrepancy between the results shown by Tam et al. (2001) and the calculations could be attributed to the lack of information regarding which demands are served by each supply. Tam et al. (2001) mention the best supply locations in their manuscript, but they do not discuss whether the supply locations supply all nine demand points or specific ones.

Table 6. Total Costs For Tower Crane Location 2 For All Material Types

Total Cost:											
						To					
		D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	
From	**S1**	9.61	9.96	8.60	8.31	6.44	5.91	6.71	6.80	6.25	
	S2	5.90	7.17	8.07	7.77	5.97	9.62	7.24	4.83	4.64	
	S3	5.35	7.05	7.95	7.65	9.52	13.16	7.44	5.03	4.82	67.97
	S4	5.31	6.44	7.33	8.91	12.92	13.97	9.12	7.85	8.41	
	S5	8.63	8.28	10.78	12.02	13.88	14.93	12.70	11.44	11.99	

	S6	11.77	11.41	12.30	12.59	14.45	15.50	15.84	14.57	15.13	
						To					
		D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	
From	**S1**	19.21	19.92	17.20	16.61	12.89	11.83	13.41	13.60	12.50	
	S2	11.81	14.34	16.13	15.55	11.94	19.23	14.47	9.67	9.27	122.42
	S3	10.71	14.10	15.89	15.31	19.03	26.32	14.88	10.07	9.64	
	S4	10.63	12.88	14.67	17.81	25.83	27.93	18.24	15.71	16.82	
						To					
		D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	
From	**S5**	25.90	24.83	32.35	36.05	41.64	44.79	38.11	34.31	35.98	
	S6	35.31	34.24	36.89	37.77	43.36	46.51	47.52	43.71	45.38	
	S7	40.76	36.31	33.62	34.50	40.08	43.24	52.97	49.17	49.00	
	S8	24.88	25.95	18.43	16.43	20.92	24.07	41.86	38.06	29.84	
	S9	26.27	27.35	19.83	16.28	15.06	20.76	40.17	29.66	16.65	212.02
										Σ =	402.41

Results and Discussions

Using the modified formulation, a pheromone evaporation rate of 0.4, 2 iterations, 250 ants, and α and β values of 0.2 and 0.4, respectively, the best tower crane location was found to be position eight with supply points two, one, and five, which resulted in a total cost of $507.24. The best values for the 12 tower crane locations can be found in Table 7. Using the modified formulation, alpha and beta parameter values of 0.25 and 1, respectively, and the authors' tower crane location of two with supply points three, two, and nine, the total costs are $540.76. Using these values as comparison, the reconstructed ACO model provided a better solution than GA ($540.8) should the correct formulation and original parameter values be used.

Table 7. Best Ant Solution Per Nest for Tam et al. (2001) ACO Model

Total Population: 6000	
Ants per nest: 500	
TC Location	Best Ant Value
8	507.24
2	509.43
3	516.46
6	518.37
7	526.14
4	528.69
9	533.18
5	536.09
11	537.03
10	544.01
1	545.18
12	558.89

Furthermore, Table 8 displays the output for two distinct α and β scenarios as well as the two angular formulations. It can be seen that neither of the two different scenarios accurately account for the results outlined in the original manuscript. Nevertheless, this is to provide further information that might serve useful for researchers attempting to replicate their model and results.

Table 8. Results Comparison Using Alternate Values Of α And β (Tam et al., 2001)

	Corrected Formulation	**Authors' Formulation (Tam et al., 2001)**

Hoisting Velocity, V_h, (rad/min)	Radial Velocity, V_a, (rad/min)	Slewing Velocity, V_ω, (rad/min)	C_{jk} ($)	α	β	Best Tower Crane Location	Total Costs, TC ($)	Best Tower Crane Location	Total Costs, TC ($)
60	53.3	7.57	$1.92	1	0.25	2	437.09	2	402.41
60	53.3	7.57	$1.92	0.25	1	8	507.24	2	489.04

Huang et al. (2011)

The next ACO model is based on the model from Huang et al. (2011). In their work, Huang et al. (2011) optimized the tower crane location and its surrounding supply facilities by considering the concept of homogeneous and non-homogeneous supply locations. Homogeneous locations are facilities that can only store one material type while non-homogeneous points can house multiple different types of materials. These non-homogeneous supply points could allow savings in transportation time by granting the crane the option of using the same supply point for multiple demands.

Huang et al. (2011) also based their mathematical formulations on the work of Zhang et al. (1996). The objective function, however, includes an additional parameter γ. This factor accounts for additional time delays due to potential difficulties experienced by the crane operator. Events such as a highly congested construction area or bad weather conditions might hinder the operator's ability to operate at normal pace, and γ is used to accounts for this additional time. This factor can have any value between "0.1" and "10", but it will be kept as "1" to assume normal conditions like in the original model. The author's objective function will be used for the reconstructed model, and it can be seen in Equation 39.

$$T_{i,j}^{k} = \gamma\{Max(T_{hij}{}^{k}, T_{vij}) + \beta * Min(T_{hij}{}^{k}, T_{vij})\} \quad (39)$$

The case study used by Huang et al. (2011) was the same as the one developed by Tam et al. (2001), which means that the ACO model will be considering 12 ant nests that represent the 12 different tower crane locations. The same discrepancy with the α and β values found in the model by Tam et al. (2011) can be found in this work. No clear indication of why it was done could be found in the original manuscript, but the ACO model will consider the values from the work of Zhang et al. (1999).

The ant in the ACO model undergoes a small change from the one presented for Tam et al. (2001). Previously, the material types A1, A2, and A3 were not carried by all nine supplies. However, in this model all supplies can carry the three material types; but the ant still cannot select the same supply point for multiple material types. The ant model used for this work can be seen in Figure 23b.

Verification of Results

The results obtained by Huang et al. (2011) were verified using the same procedure previously discussed for the model of Tam et al. (2001). The initial calculations confirmed their optimal tower crane location as well as their total costs of $504.76. However, it is of substance to mention that their results were confirmed using the correct angular formulation and the original alpha and beta parameter values of 0.25 and 1, respectively. This is significant because Huang et al. (2011) call out the incorrect formulation and switched the alpha and beta values in their manuscript, which would not match the output they provided in their manuscript.

Results and Discussions

The ACO model based on the work of Huang et al. (2011) considered the 12 tower crane locations as nests. The ant parameters that provided the best results were an ant population of 650 per nest, and evaporation rate of 0.4, reward factor of 100, 2 iterations, and α and β of 2.6 and 1.2, respectively. Table 9 summarizes the optimal values for each tower crane location. The best tower crane location resulted in position eight with a total cost of $504.76, which was the same cost value determined by mixed integer linear programming (MILP) model. Although

ACO did not produce more optimal results than MILP, it is valuable to know that ACO can provide the global optimum solution to allocation problems such as this one.

Table 9. Best Ant Solution Per Nest For Huang et al. (2011) ACO Model

	Best Ant			
Nest	M1	M2	M3	Best Value
8	2	5	1	504.76
3	6	2	1	507.02
2	9	4	8	508.28
7	9	5	4	514.40
6	3	2	8	518.37
4	5	4	8	528.69
5	8	2	1	528.89
9	6	3	1	529.58
11	4	5	8	531.26
1	6	9	1	538.92
10	5	8	4	541.44
12	9	5	1	558.45

In addition, Table 10 is presented here to provide a similar purpose as Table 8. Huang et al. (2011) displayed their output in their manuscript along with their α and β parameter values. However, it is only possible to attain the optimal tower crane location and costs of “8” and “504.76”, respectively, using α of 0.25 and β of 1. Thus, this information is meant to aid anyone attempting to replicate their results.

Table 10. Results Comparison Using Alternate Values Of α And β (Huang et al., 2011)

							Corrected Formulation		Authors' Formulation (Huang et al., 2011)	
Hoisting Velocity, Vh, (rad/min)	**Radial Velocity, Va, (rad/min)**	**Slewing Velocity, Vω, (rad/min)**	**Cjk ($)**	**α**	**β**	**γ**	**Best Tower Crane Location**	**Total Costs, TC ($)**	**Best Tower Crane Location**	**Total Costs, TC ($)**
60	**53.3**	**7.57**	**$1.92**	**1**	**0.25**	**1**	**2**	**434.92**	**2**	**388.16**
60	**53.3**	**7.57**	**$1.92**	**0.25**	**1**	**1**	**8**	**504.76**	**2**	**480.19**

Moussavi Nadoushani et al. (2016)

The final ACO model that was developed was based on the model done by Moussavi Nadoushani et al. (2016). In their work, the authors accounted for the impact material loads have on rental and operating costs of the crane. The authors considered 968 demand points, six supply points, and six possible tower crane positions, where the objective was to find the best tower crane location that minimizes the total cost incurred by the crane (which include rental and operating costs). The authors opted to use MILP, and the reconstructed model considers the same constraints as the original model.

The ant model used in this reconstructed model is distinct from the previous ones in the manner it handles the demand points. In the previous reconstructed models, the ant size could be as long as the number of demand points to allow the ant to select and optimize the supply points for each demand point. However, because there are 968 demand points in this work, the ant size would be excessively large unless there is a step implemented to reduce it prior to the optimization process. Thus, the reconstructed ACO model in this work considers an additional step where demands are preemptively assigned to supply points based on proximity. Given a specified proximity distance, the algorithm assigns demand points to the supply points closest to them. However, there will be demand points that are situated outside the range of all supply points. These demand points – denominated as “Border Points” – are the ones in need of an optimized supply assignment, and the number of these demand points will constitute as the ant size.

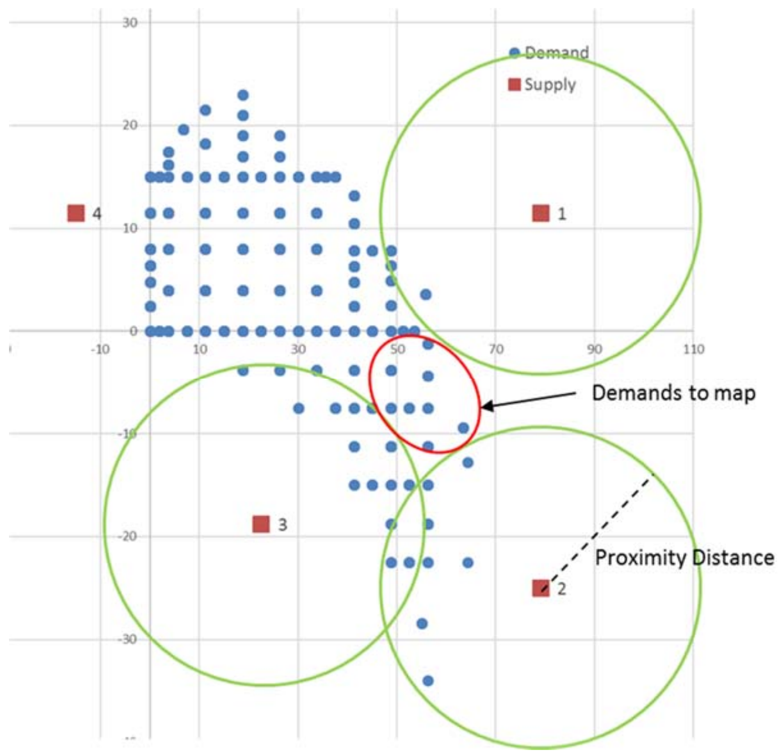


Figure 24. Demand Points (Border Points) In Need Of Optimized Pairing

Figure 24 illustrates the site plan for this model and its border points given an arbitrary proximity. The proximity distance is shown as circles of radius equal to the proximity, and remaining demands outside the proximity ranges can be seen as well. Further, Figure 25 showcases an illustrative representation of the ant model used in ACO.

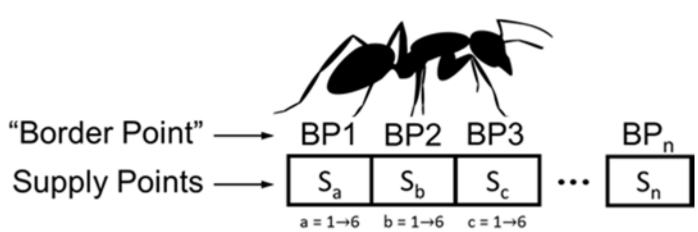


Figure 25. Ant Model For Optimization Of Border Points

Verification of Results

The work of Moussavi Nadoushani et al. (2016) was first verified before the development of the ACO model. This was done through the creation of a MILP model created under the same environment as the authors (IBM CPLEX) and ran using the original formulations. The output from the model in comparison to the original results can be observed in Table 11, and the performance difference for each of the crane locations is illustrated in Figure 26.

Table 11. Results Of Developed Model Against Original CPLEX Model

Tower Crane Location	CPLEX Model		Original Model (Moussavi Nadoushani et al., 2016)		% Error
	Total Travel Time (min.)	Objective Function Value (AUD)	Total Travel Time (min.)	Objective Function Value (AUD)	
1	662.50	3047.50	609.31	2802.83	8.73
2	673.03	4105.46	1032.63	6299.04	34.82
3	659.84	4025.00	1028.04	6271.04	35.82
4	688.95	5236.03	1081.16	8216.82	36.28
5	673.17	3433.16	1016.15	5182.37	33.75
6	693.60	4230.95	1086.52	6627.77	36.16

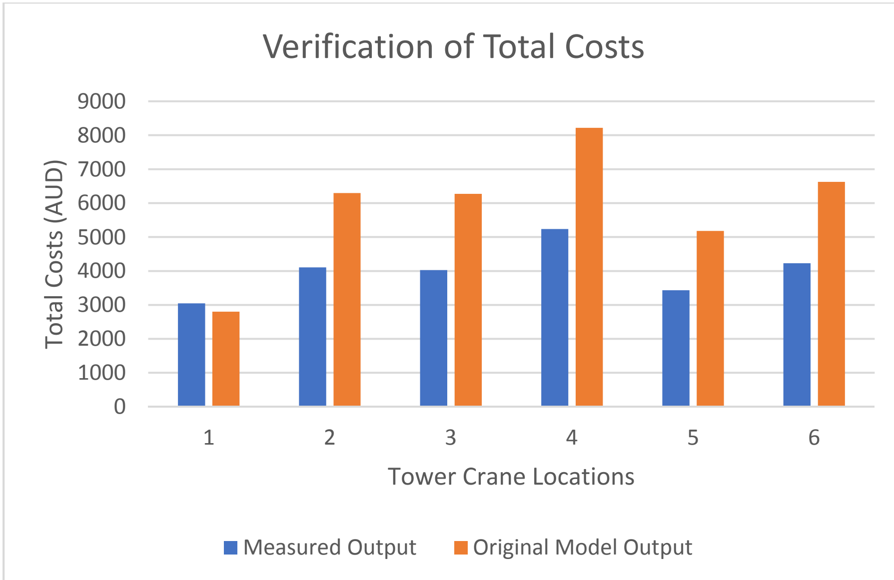


Figure 26. Comparison Of Total Costs Between CPLEX Models

Both MILP models obtained tower crane location "1" as the most optimal in terms of costs. However, the objective function values differ significantly for the other crane positions, supported by the percentage of error. From additional investigations and calculations done in spreadsheets, the discrepancy was found in the angular travel time output. The results from the spreadsheet calculations and the CPLEX output for the angular travel time are shown in Table 12. The slight difference per individual calculations, which could be attributed to how CPLEX calculates trigonometric functions, over a large margin could explain the overall variance between the two models' results. It should also be mentioned that the developed CPLEX model found the same feasible supply points as the original model from the authors, with the exception of supply six also being feasible.

Table 12. Angular Travel Time Calculations VS CPLEX Output

			Angular Travel Time		Total Travel Time	
Supply	Demand	Tower Crane Location	Value (CPLEX)	Value (Calculations)	Value (CPLEX)	Value (Calculations)

1	1	1	0.202	0.182	1.964	1.959
1	2	1	0.202	0.114	2.182	2.160
1	3	1	0.202	0.201	1.991	1.990
1	4	1	0.202	0.140	2.237	2.221
1	5	1	0.202	0.244	2.014	2.024
1	6	1	0.203	0.244	2.295	2.305
1	7	1	0.199	0.286	1.990	2.012
1	8	1	0.192	0.347	2.234	2.273
1	9	1	0.199	0.321	1.928	1.958
1	10	1	0.196	0.390	2.120	2.168

For additional reference, Table 13 contains the output from the CPLEX model should the correct formulation be incorporated. Although the same tower crane position is selected, the costs are greater in comparison to using the mistaken angular formulation.

Table 13. CPLEX Output Using Correct Angular Travel Time Equation

Tower Crane Location	Total Travel Time (min.)	Objective Function Value (Total Costs)
1	671.4803	3088.809
2	677.799	4134.574
3	665.2763	4058.186
4	693.0835	5267.434
5	681.5703	3476.009
6	698.6316	4261.653

Results and Discussions

The parameters values that were utilized in the reconstructed ACO model were a proximity distance of 31.5 (which resulted in 24 demand points in need of assignment), pheromone reward, *R*, of 1, a pheromone evaporation rate, ρ, of 0.4, number of iterations, *t*, of 3, number of ants per nest of 100, α value of 1.6, and β value of 1.0. The results of 10 runs are shown in Table 14, where the best solution of 3,558.05 (AUD) using tower crane location "1" was obtained. In comparison to the results obtained by Moussavi Nadoushani et al. (2016), the ACO model did not outperformed the MILP model, but ACO was ran with the correct angular formulation. Thus, in comparison to the results shown in Table 13, ACO appears to provide more similar results than the authors. This could support the premise that the results from the original model – the authors' – were based on the mistaken angular travel time equation.

Table 14. ACO Model Output

	ACO	
Trial	Global Best Ant (AUD)	TC Location
1	3559.244	1
2	3558.943	1
3	3559.587	1
4	3558.943	1
5	3559.244	1
6	3558.943	1
7	3558.943	1
8	3559.835	1
9	3558.943	1
10	3558.052	1

AVG	3559.068

Conclusions

The tower crane allocation problem presents a special challenge to managers and planners day by day. Many research works have contributed models and techniques used to appropriately optimize the tower crane location in construction sites. However, while the tower crane allocation literature is rich in contributions, some issues and discrepancies limit many tower crane allocation models. In addition, ACO has been largely omitted as a means of optimization to this problem despite its effectiveness with other optimization problems. The reconstruction of some models was performed to address the original issues, verify results, and for ACO implementation. Results show that ACO is just at optimal or more in comparison to other optimization techniques used in the literature, such as GA and MILP. Future work on this topic includes the development of a framework with building information modeling (BIM) and ACO, as well as the application of other powerful artificial intelligence techniques to the reconstructed models.

CHAPTER IV

MODIFIED ACO FOR TOWER CRANE ALLOCATION PROBLEMS

Introduction

In the construction industry, many different types of equipment are used for the realization of successful projects. Cranes are an important class of equipment that grant needed power and abilities to accomplish curial tasks during construction. Tower cranes, in particular, are primarily used for the transportation of material across the site and have become prominent in countless job sites due to their greater hoisting capacities, higher reach, and ability to perform its duties without large amounts of space. However, due to the high costs associated with the crane, managers are in need of relying on other methods, aside from their experience alone, to determine the best location such that costs and delays are minimized. This is known as the tower crane allocation problem. In the past, researchers have developed methodologies and approaches aimed at optimizing the tower crane location in construction sites (Abdel-Khalel, Shawki, & Adel, 2013; Abdelmegid, Shawki, & Abdel-Khalek, 2015; Alkriz & Mangin, 2005; Choi & Harris, 1991; Furusaka & Gray, 1984; Huang, Wong, & Tam, 2011; Izarry & Karan, 2012; Lee, Lim, Cho, & Kang, 2015; Lien & Cheng, 2014; Marzouk & Abubakr, 2016; Moussavi Nadoushani, Hammad, & Akbarnezhad, 2016; Rodriguez-Ramos & Francis, 1983; Tam, Tong, & Chan, 2001; Tam & Tong, 2003; Tubaileh, 2016; Wang et al., 2015; Zhang, Harris, & Olomolaiye, 1996; Zhang, Harris, Olomolaiye, & Holt, 1999). However, through careful analysis, it was found that many of the past works contain critical flaws in their models. In addition, some powerful approaches used, such as Ant Colony Optimization (ACO) (Trevino & Abdel-Raheem, 2017a), lack efficiency when dealing with many possible tower crane locations – a special type of tower crane allocation problem (Trevino & Abdel-Raheem, 2017b). Thus, this research presents an alteration to the well-known ACO approach used to effectively and efficiently solve these special tower crane allocation problems.

Objectives

The primary objectives of this research are the development of a modified ant colony approach (MACA) and its implementation to certain reconstructed models from the literature. These reconstructed models consider the special variation of the tower crane allocation problem and are based on the works of Tam et al. (2001), Huang et al. (2011), and Moussavi Nadoushani et al. (2016).

Methodology

This research originated from the initial goal of developing a comprehensive tower crane allocation framework, which included the use of Building Information Modeling (BIM), that could serve as a tool for managers and personnel in the construction industry. However, while performing thorough examinations of past works in the literature, it was found that many of the past models had inconsistencies, discrepancies, and flaws. Many of these were in the form of incorrect formulations (Trevino & Abdel-Raheem, 2017a; Trevino & Abdel-Raheem, 2017b), missing information, parameter value discrepancies, and confusing terminology. As a result, previous models were reconstructed (addressing the issues found on previous models) and ACO was applied as the means of optimization. However, upon closer inspections of the algorithm optimization process, it was discovered to contain a limitation when subject to some tower crane allocation problems. These allocation problems contain numerous possible tower crane locations, which require the algorithm to consider them as separate nests independent of each other. This separation and lack of inter-communication between the nests makes the algorithm significantly inefficient since the nests do not communicate nor cooperate to find an optimal solution. Thus, it became important to account for this weakness exhibited by the algorithm, and use the new version of ACO to optimize some of the reconstructed models from the literature.

To achieve the objectives, the methodology employed begins with the careful study of the literature and past models. Documentation of limiting factors, such as errors, inconsistencies, and discrepancies, was then performed. Models were reconstructed to address the limitations of past works and ACO was utilized for optimization. The incorporation of an ant agent – noted as the "Lead Ant" – was then implemented into ACO to create an ACO variation fitted for special type of tower crane allocation problems. Comparisons were made between the two optimization approaches, and conclusions were drawn and discussed.

Past Models

The optimization of tower crane location has attained a significant amount of attention from researchers over the last 30 years. Many of the past works focused on the optimization approaches, improving the tower crane allocation model, and incorporating the benefits of new technological trends into comprehensive tower crane allocation frameworks, such as building information modeling (BIM). Rodriguez-Ramos and Francis (1983) were the first to introduce a mathematical model used to optimize the location of a single tower crane. Their crane model considered both the angular and trolley movements of the crane hook, and the authors used a graphical approach to determine the best tower crane location in terms of minimum hook travel time. Furusaka and Gray (1984) created a crane model capable of selecting the appropriate crane types needed as well as their location in the construction site. Choi and Harris (1991) improved the tower crane model from Rodriguez-Ramos and Francis (1983) by considering the frequent movements performed by the crane to its surrounding facilities. Zhang et al. (1996) published an important model that utilized Monte Carlo simulation to replicate the potential sequence of deliveries of the crane. The authors' improved mathematical model accounted for the horizontal movements with greater accuracy, and would become the principal basis for future mathematical models in the literature. Zhang et al. (1999) provided an expansion to their past model by including the vertical, hoisting times of the hook as well as the inclusion of multiple cranes on site. Tam et al. (2001) commenced usage of a genetic algorithm (GA) used to optimize the supply locations around the crane. In addition, their study introduced actual velocity values from site observations and a case study that many future researchers would use to test their approaches. Tam and Tong (2003) elaborated on the work from Tam et al. (2001) by providing a model that combined artificial neural networks (ANN) with genetic algorithms (GAs). Their framework allowed statistical approximations of the hosting time values and optimization of the facility locations. Alkriz and Mangin (2005) granted an additional GA model that accounted for multiple cranes, collision checks, and crane cycles. Huang et al. (2011) contributed a mixed integer linear programming (MILP) model used to optimize the location of a single tower crane and its surrounding facilities. Further, their optimization model considered homogeneous and non-homogeneous material supply points, which proved to outperform GA. Irizarry and Karan (2012) presented a framework that considered both BIM and Geographic Information System (GIS) to position tower cranes. Abdel-Khalel et al. (2013) published a GA model that improved on the work from Alkriz and Mangin (2005) by providing an update to the vertical hook travel time component. Abdel-Khalek et al. (2013) separated the total hook hoisting time into two components – loaded hook and unloaded hook vertical travel times – to consider a more exact representation of what occurs in the field. Lien and Cheng (2014) made a hybrid optimization approach, encompassed of Bee Algorithm (BA) and Particle Swarm Optimization (PSO), called Particle Bee Algorithm (PBA) used to optimize the material quantities required between supply and demand facilities. Sohn et al. (2014) created a model that focused on determining the best tower crane type while considering its foundation design and lateral support. Zavichi, Madani, Xanthopoulos, and Oloufa (2014) utilized their developed approach to optimize the service requests of the crane based on the Traveling Salesman Problem (TSP). Abdelmegid et al. (2015) developed an additional GA model and improved the tower crane allocation model by accounting for the number of crane cycles, loading and unloading hook travel times, and tower crane base constraints. Lee et al. (2015) introduced a tower crane allocation model for the luffing boom type of tower crane that concentrated on the movements exhibited by this specific crane configuration. With regards to more visualization, Wang et al. (2015) established a tower crane allocation framework made up of BIM and Firefly Algorithm (FA). Their FA approach optimized the tower crane location and surrounding facilities while BIM was used to visualize the output. In addition, Marzouk and Abubakr (2016) created a similar framework that considered the visual capabilities of BIM while using GA to optimize. The model developed by Monghasemi, Nikoo, and Adamowski (2016) optimized the time spent between requests. Tubaileh (2016) presented kinematic and dynamic models as improvements to the allocation model. Moussavi Nadoushani et al. (2016) further improved the allocation model by considering the impact material loads have on the total costs of the crane. Trevino and Abdel-Raheem (2017a) presented an ACO model to allocate a single tower crane, resulting in performance comparable to MILP. Furthermore, Trevino and Abdel-Raheem (2017b) updated their ACO model to account for a limitation when dealing with multiple tower crane locations. Their modified ACO approach proved to determine the global optimal solution in a shorter time in comparison to traditional ACO.

Limitations and Shortcomings of Previous Models

As seen in the previous section, the literature contains numerous contributions to the tower crane allocation problem. However, many works contain critical errors, flaws, confusing terminology, and, in some cases, lack important details and information. Rodriguez-Ramos and Francis (1983), Furusaka and Gray (1984), Choi and Harris (1991), and Zhang et al. (1996) did not account for the vertical, hoisting movement of the crane in their models. In addition, the model presented by Furusaka and Gray (1984) considered the usage of multiple cranes but did not account for possible collisions between them. Choi and Harris (1991) optimized the tower crane location from a predetermined set of four locations, which leaves out other possible locations within proximity that could further reduce the costs. The model of Zhang et al. (1996) contains a critical error in the angular movement formulation, noted by Trevino and Abdel-Raheem (2017a). This oversight outputs slewing times based on supplementary angles created by the facilities, which could overestimate and underestimate the time. In addition, many works have carried and used this flawed formulation in their models (Alkriz & Mangin, 2005; Huang et al., 2011; Lee et al., 2015; Lien & Cheng, 2014; Moussavi Nadoushani et al., 2016; Tam & Tong, 2003; Tam et al., 2001; Want et al., 2015; Zhang et al., 1999). Zhang et al. (1996) also mentioned using an effective algorithm to determine feasible areas, but they do not provide details or explanations concerning the algorithm process. The values of important parameters, α and β, were called out in switched order in some works (Huang et al., 2011; Lien & Cheng , 2014; Tam et al., 2001; Tubaileh, 2016) from the original values set by Zhang et al. (1999) without explanation. The parameter value changes could create potential difficulties for researchers attempting to replicate the results from the literature. The manuscript by Irizarry and Karan (2012) does not contain explanations or illustrations of the cost and objective functions. Similarly, Abdelmegid et al. (2015) did not clearly explained their objective function and its relationship to their proposed improvements. The optimization model created by Moussavi Nadoushani et al. (2016) considered material quantities but the authors do not clarify the parameter value used in their model. Further, due to space limitations, the authors only provided a small piece of demand point data in their manuscript, which, though a small limiting factor, might impede replication of their results. Trevino and Abdel-Raheem (2017a) utilized ACO to optimize tower crane location but the approach has limitations when dealing with multiple tower crane locations. This is because each location must be treated as a different nest by the algorithm, and, because there is no intercommunication between the nests, all nests receive the same quantity of ants regardless of their merit. As an example, Figure 27 illustrates various nests and a food source. The distance between the food source and nests varies. However, assuming all nest are interconnected and cooperate with each other, it would be logical for Nest 3 to send out more ants since it is the closest to the food source. This would create a more efficient system when searching the solution space.

Thus, the modified approach – entitled Modified Ant Colony Approach (MACA) – will be used for the reconstructed ACO models from the literature, and performance comparisons between ACO and MACA will be made to assess the usability of the approach.

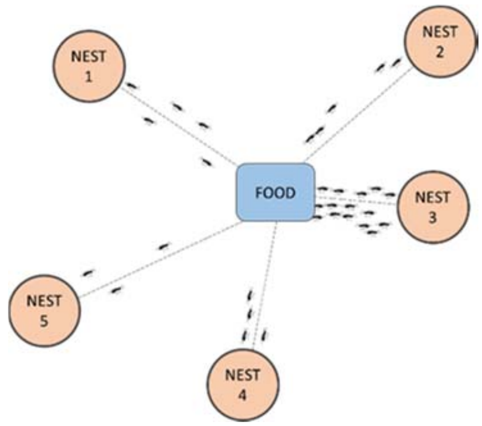


Figure 27. Ant Nests And Their Distance Relative To Food Source

ACO Background

Ant colony optimization (ACO) is a swarm-based artificial intelligence technique developed by Marco Dorigo in 1992 that mimics ant colonies in their search for food sources. As the ants scout the nearby area in search of food, they leave behind chemical substances known as pheromones. Since the ants are mostly blind, these pheromone trails act as a guide for the ants to return back to the nest. The ants that encounter the food first – the ones closer to the food source – return to the nest faster than other ants while depositing more pheromone. Eventually, the pheromone on the shortest trail becomes strong enough to be perceived by other nearby ants, and they gradually converge towards the shortest path. Figure 28 illustrates the concept behind ACO and the convergence.

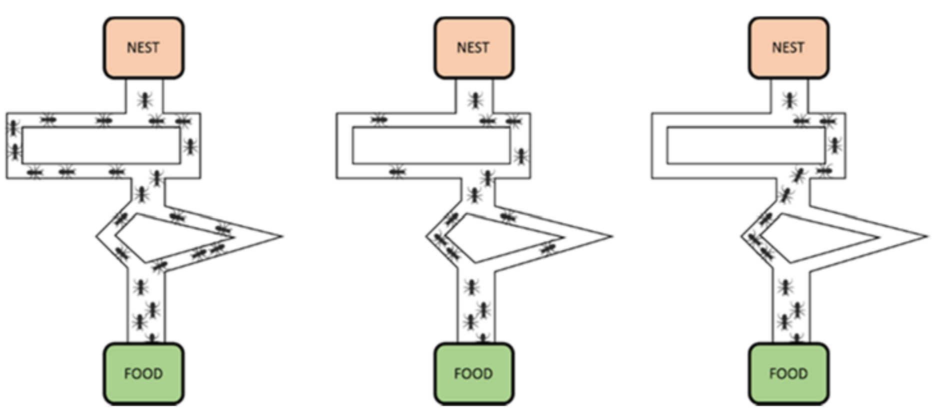


Figure 28. ACO Progression

In application, the algorithm follows six principal steps as noted by Abdel-Raheem et al. (2013): 1) Generation of solutions, 2) Heuristic information, 3) Evaluation, 4) Pheromone update, 5) Probability update, and 6) Termination. A flowchart of the ACO approach can be seen in Figure 29.

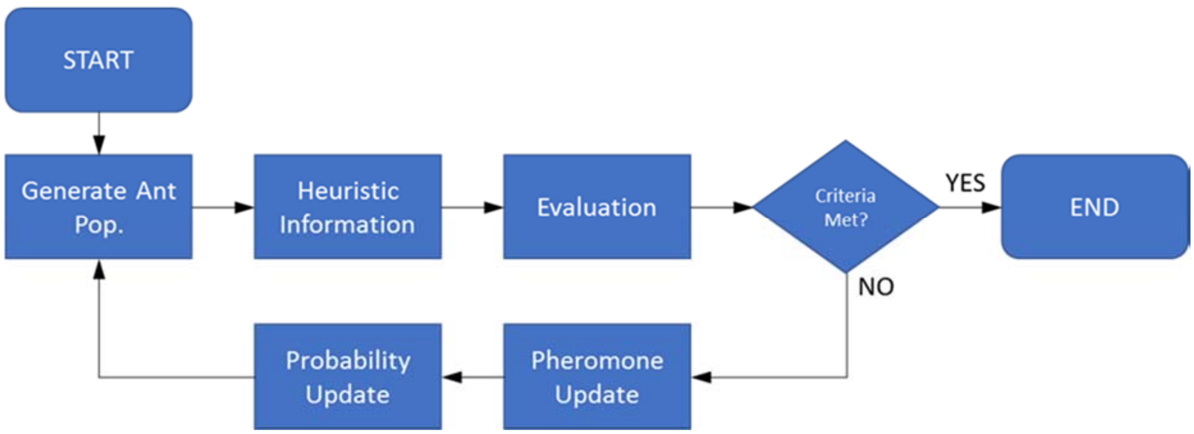


Figure 29. Typical ACO Flowchart

Modified Ant Colony Approach (MACA)

ACO has been proven to be an effective optimization approach to many problems, including tower crane allocation (Trevino & Abdel-Raheem, 2017a). However, a key weakness is the lack of communication between the agents of the approach – the nests (Trevino & Abdel-Raheem, 2017b). The new approach presented in this work, MACA, is based on the same steps performed by traditional ACO with the addition of an ant agent denominated as "Lead Ant". This ant can be pictured as an ant queen that receives information from all the nests in the colony. An illustration of this premise can be seen in Figure 30.

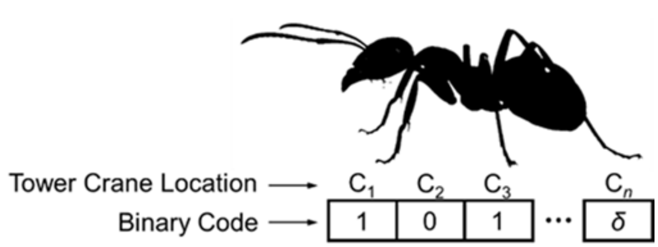


Figure 30. Lead Ant Model

Therefore, this concept is based on the assumption that all nests are interconnected and cooperate with each other to attain a common goal. As ants perform their search, the lead ant collects the performance information from each of the nests and ranks them accordingly. Afterwards, based on the performance, the lead ant redistributes the ant population in such a way that nests with higher performance – better ant solutions – receive a greater portion of it. A flowchart of the methodology can be seen in Figure 31. This approach creates a system with more efficient utilization of resources when multiple nests are required.

Abdel-Raheem et al. (2013) described the essential six steps of traditional ACO. In MACA, during the generation of the ant solution, the approach creates a lead ant as well. The lead ant can be modeled as a binary agent that directs whether or not to give ants to the nets. A "0" represents an empty nest in need of ants and a "1" describes a nest with ants.

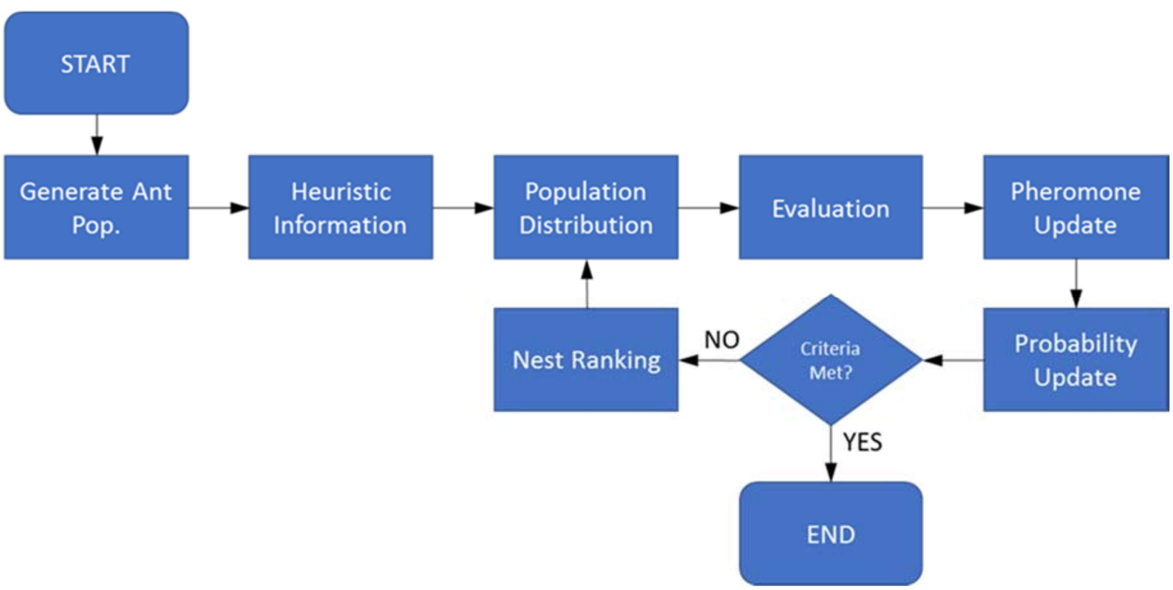


Figure 31. MACA Flowchart

Case Studies

The literature contains numerous case studies and numerical examples used to evaluate the performance of optimization approaches. However, as previously discussed, a high percentage of past models contain errors and flaws that hinder the models' usability. Therefore, three research works – Tam et al. (2001), Huang et al. (2011), and Moussavi Nadoushani et al. (2016) – were selected and their models were reconstructed to implement generic ACO and MACA as means of optimization. These research works considered multiple tower crane locations, which required the use of multiple nests to optimize.

Tam et al. (2001)

The first model in the series of works that considered numerous tower crane locations was originally developed by Tam et al. (2001). The authors presented an elaborate tower crane model allocation model that considered multiple material types, velocities from actual observations, and genetic algorithms. However, the main problem in their model was the incorporation of the incorrect angular travel time formulation, incorrect descriptions of GA, and discrepancies with results.

Much like the ACO model described in Chapter III, the ant in MACA consists of three variables that store the supply points for each material type. However, it is important to note that the pheromone update is performed per nest, and supply points chosen by ants of different nests do not accumulate pheromone for those points. For example, if an ant in Nest 1 selects supply 1 for its first variable, as shown in Figure 32, an ant in Nest 2 that selects supply 1 for its first variable will not be adding pheromone to that same option. The supply points' pheromone would be different for all nests regardless if the ants from different nests select the same supply points.

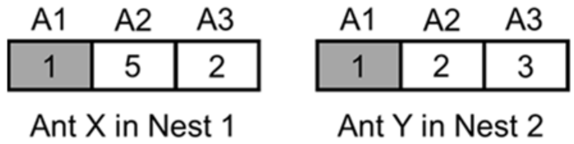


Figure 32. Pheromone Repetition Example In Two Nests

Both the ACO and MACA model ran in the same machine with the same parameters. Both incorporated a pheromone reward factor, R, of 1, a pheromone evaporation rate, ρ, of 0.4, number of ants per nest of 15, α value of 0.2, and β value of 0.4. The heuristic information for MACA was based on the same concept as ACO. Further, both approaches were directed to run and iterate until the global best solution was reached. Table 15 summarizes the findings between the two approaches in ten trials.

Table 15. Output Comparison Between General ACO And MACA

	General ACO			MACA		
Trial	Time (s)	Iterations	Ants	Time (s)	Iterations	Ants
1	3.54	10	1,800	1.16	3	542
2	3.05	9	1,620	0.84	2	361
3	3.30	10	1,800	1.63	4	722
4	4.00	12	2,160	2.23	6	1,081
5	2.09	6	1,080	0.86	2	360
6	8.88	31	5,580	1.67	4	720
7	0.45	1	180	5.66	18	3,241
8	7.05	24	4,320	0.88	2	360
9	4.63	13	2,340	0.48	1	180
10	3.16	8	1,440	1.91	4	721

In addition, Figure 33 presents the average optimization times of the 10 runs for the two approaches. As shown in the illustration, the average time of the 10 runs using basic ACO was approximately twice as long in comparison to MACA. These results support the hypothesis that MACA would run under a more efficient system by reinforcing the locations or nests closer to the global best solution. As a result, it was expected to reach optimum solutions at a faster rate.

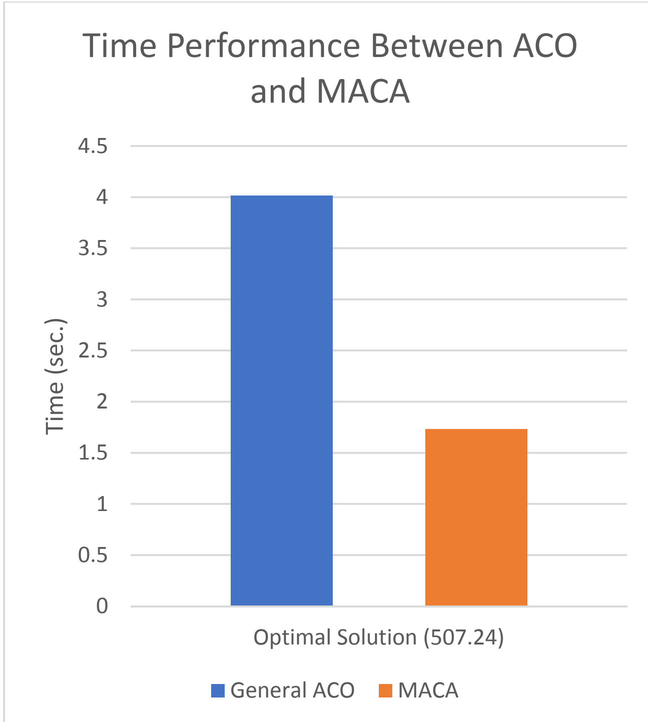


Figure 33. Output Performance Between ACO And MACA (Tam et al., 2001)

Huang et al. (2011)

The second model in this series was based on the work done by Huang et al. (2011). The authors' original model was based on the work of Tam et al. (2001), but it differed in that it considered cases for both homogeneous and non-homogeneous supply points, provided additions to the tower crane allocation model in the form of factors to account for the difficulties encountered by operators, and allowed all supplies to be able to carry all material types. Furthermore, Huang et al. (2011) used mixed-integer linear programming (MILP) as their means of optimization, which provided a better solution than genetic algorithms. However, there are some errors that could create difficulties for researchers attempting to replicate their work. For instance, the angular travel time formulation is incorrectly called out and the α and β parameters appear with switched order from those originally set by Zhang et al. (1999). Using the formulation and parameter values called out in their manuscript will not yield the results that are also shown in their work.

The ant created for this model is composed of three variables similar to the recreated Tam et al. (2001) ACO model. However, in this case all supply points can carry the three material types. Figure 34 shows an illustrative representation of the ant for this model.

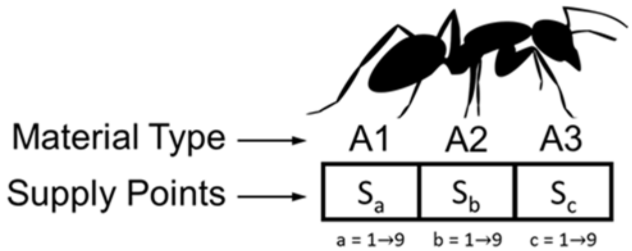


Figure 34. Ant Model For Huang et al. (2011) Recreated Model

The same pheromone rules and the heuristic information methodology presented in the previous section apply to this model as well. The parameter values used in this model were a pheromone reward, *R*, of 5, a pheromone evaporation rate, ρ, of 0.4, number of ants per nest of 15, α value of 1.6, and β value of 1.0. The results of 12 runs are shown in Table 16, and the average time spent by the algorithms can be seen in Figure 35. Much like the previous MACA model, the results show a high reduction in the average time spent by the approach before reaching the global optimum solution in comparison to basic ACO.

Table 16. Result Comparison Between ACO And MACA

	General ACO			MACA		
Trial	Time (s)	Iterations	Ants	Time (s)	Iterations	Ants
1	5.75	25	6,000	1.30	5	1,201
2	1.44	6	1,440	26.53	134	32,252

3	12.10	57	13,680	5.91	27	6,496
4	2.86	12	2,880	2.42	10	2,407
5	2.77	11	2,640	15.56	78	18,752
6	11.25	52	12,480	4.30	19	4,569
7	9.50	36	8,640	22.59	112	26,918
8	57.47	274	65,760	1.00	4	961
9	3.67	15	3,600	2.00	8	1,920
10	1.23	5	1,200	3.04	13	3,128
11	1.67	6	1,440	0.95	3	720
12	54.39	263	63,120	4.93	21	5,042

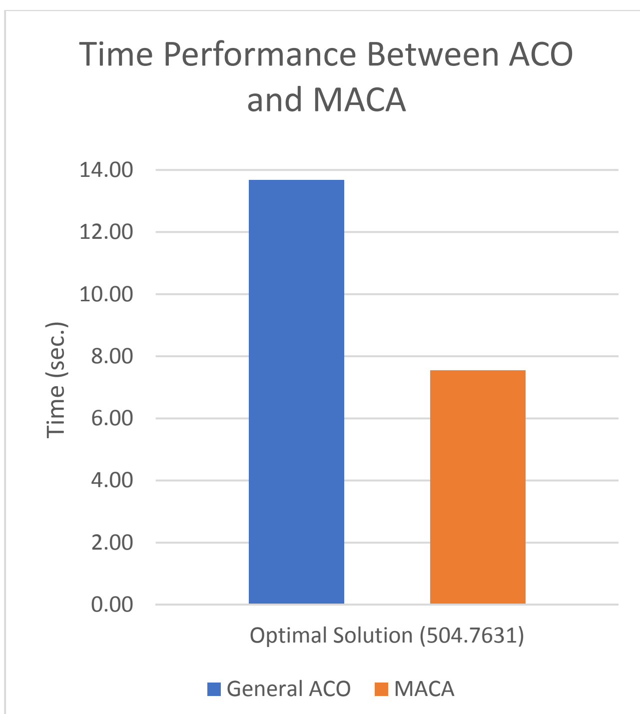


Figure 35. Output Performance Between ACO And MACA (Huang et al., 2011)

Moussavi Nadoushani et al. (2016)

The third and final reconstructed model in this section was based on the work of Moussavi Nadoushani et al. (2016). The original model developed by the authors considered the effects that loads create on the crane in terms of operating and rental costs. Their model was based on the work of Huang et al. (2011) but included additional constraints to ensure that supplies are assigned to demand points only if the loading capacity is not exceeded. Nevertheless, the authors' angular travel time formulation is illustrated with the same error as previous works, and they only provide a summary of their demand point data. While the lack of space in their publication accounts for the summarized demand point data, the error in their angular travel time formulation poses limitations in their work.

The main objective in this model is the determination of a tower crane location that minimizes the total costs incurred from rental and operating fees. The crane costs are related to the amount of time it spends servicing its surrounding demand and supply facilities. Each demand point must be assigned to at least one supply point, but the assignment must respect the load capacity of the crane. This means that an assignment between a demand and supply point can only occur if the crane is able to transport material loads between the pair without exceeding the crane's load limit.

A noteworthy consideration that was made in this model is the reduction of the ant size prior to the optimization processes of ACO. Normally, the ant could be modeled having a size equal to the total number of demand facilities. However, because there are 968 demand points, the ant size would be very high and could create potential limitations during the optimization process. In order to reduce the size of the ant, an initial mapping of demand points to supply points was performed, where demand points would be assigned to supply points located within a specific proximity from each other. This step would account for a logical way of assigning the facilities and, because it is based on proximity, also leave out demands not located within the range of any supply points. As a result, these demand points with no assignment – denoted as "Border Points" – are left to be optimized, and they would compose the size of the ant model. A visual representation of the ant model can be seen in Figure 36, and Figure 37 illustrates the concept of "Border Points" by showing the demands in need of optimized pairing.

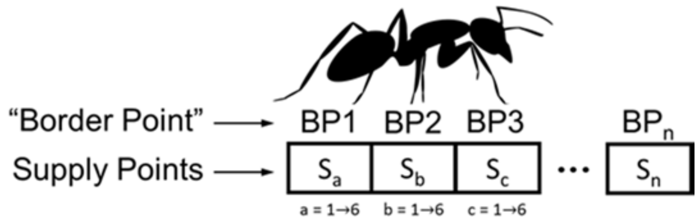


Figure 36. Border Point Ant Model

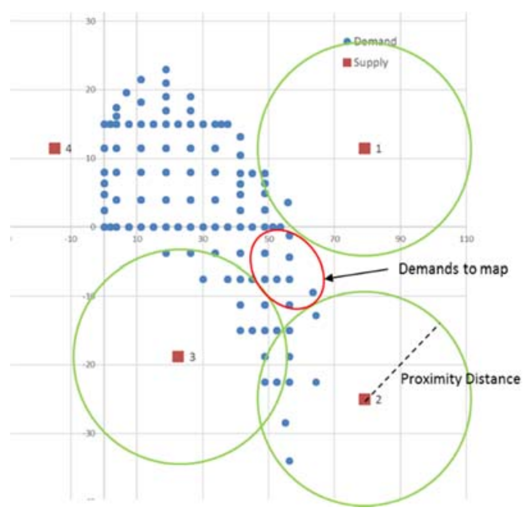


Figure 37. Demand Points In Need Of Optimized Pairing

Setting a proximity distance of 31.5 resulted in 24 border points, which lead to an ant size of 24 variables. The parameter values used in both the ACO and MACA models were a pheromone reward, R, of 1, a pheromone evaporation rate, ρ, of 0.4, number of iterations, t, of 3, number of ants per nest of 100, α value of 1.6, and β value of 1.0. The results of 10 runs is shown in Table 17, where the average total costs of ten runs is shown for both ACO and MACA. While both approaches selected tower crane location one as the best location, MACA reached overall less total costs than ACO. This means that MACA provided better assignments between supply and demand points than ACO, which allowed for less costs.

Table 17. Results Comparison Between ACO And MACA For Reconstructed Model (Moussavi Nadoushani et al., 2016)

	ACO		MACA	
Trial	Global Best Ant	TC Location	Global Best Ant	TC Location
1	3,559.24	1	3,535.99	1
2	3,558.94	1	3,534.99	1
3	3,559.59	1	3,536.57	1
4	3,558.94	1	3,535.86	1
5	3,559.24	1	3,535.46	1
6	3,558.94	1	3,536.10	1
7	3,558.94	1	3,535.79	1
8	3,559.83	1	3,536.10	1
9	3,558.94	1	3,536.57	1
10	3,558.05	1	3,534.66	1
AVG	3,559.07		3,535.81	

Conclusions

Tower cranes are essential construction equipment that require careful planning to maximize their efficiency and minimize their costs. The literature contains numerous works that have contributed tower crane allocation models with a number of optimization techniques.

However, many works are limited by flaws encountered in the models. In this work, models from the literature were reconstructed to account for the limitations of the original models, and a new approach, based on the ant colony optimization (ACO) technique, was developed and used as means of optimization. The performance of MACA was compared to ACO and the results highlight a higher performance when using MACA for all the reconstructed models. Future research possibilities include the utilization of MACA for the optimization of multiple tower cranes on site, as well as the incorporation of building information modeling (BIM) to create a comprehensive framework for construction managers and planners.

CHAPTER V

CONCLUSIONS AND FUTURE WORK

The research presented in this work offers significant contributions to the fields of construction management and operations research. The tower crane's natural tendency of being fixed to a specific position presents managers and planners with an interesting dilemma, known as the tower crane allocation problem, that affects both time and money. These two factors are critical considerations to take in any real-life problem, application, or project, and they will always demand managers to make educated and efficient decisions. The tower crane allocation literature contains numerous works that have contributed optimization models to effectively solve this problem. This research work, however, contributed critical information concerning the weaknesses and limitations of previous tower crane allocation models, which is valuable to any researcher attempting to develop allocation models or frameworks.

Furthermore, this work presented the first known application of the widely-known ACO approach specifically tailored to solve single tower crane allocation models. ACO has been known as a popular optimization technique, and its performance has shown to be reputable for known NP-Hard problems, such as the Traveling Salesman Problem (TSP). The developed ACO tower crane allocation models proved to have better or equal performance compared to the approaches used in the literature.

Moreover, a new ACO-based optimization technique, titled "Modified Ant Colony Approach" (MACA), was developed and presented in this work as an additional means to optimize the tower crane location. This approach was created to account for the weaknesses of ACO when subject to certain types of tower crane allocation problems. MACA is a valuable contribution that could potentially serve researchers with a performance benchmark for their approach, or as background for the development of techniques based on its concept. MACA demonstrated to outperform ACO in all the recreated models presented in this work, which proved the theory of it having a more efficient resource management system than ACO.

As a result of this research, future work includes the consideration of multiple tower cranes on site, the implementation of new trends, such as Building Information Modeling (BIM), and the consideration of using MACA for other optimization problems.

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BIOGRAPHICAL SKETCH

Carlos Abelardo Treviño was born in Reynosa, Tamaulipas on March 11, 1991. The first 10 years of his life he spent living in the small town of Gustavo Díaz Ordaz, Tamaulipas before moving to Mission, Texas, during his sixth grade. After attending John H. Shary Elementary, B. L. Gray Junior High School, and Irene Garcia Middle School, he went on to South Texas Business Education and Technology Academy (BETA) where he graduated in 2009. While there, he learned valuable skills in the field of education and teaching during his last two years of high school. He went on to attend The University of Texas Pan-American in Edinburg, TX with the initial goal of earning a Mathematics degree. After finding an interest in the engineering discipline in 2010, he went on as a Civil Engineering student and obtained a Bachelor's of Science in Civil Engineering in the spring of 2015. After graduating, he went to graduate school at the University of Texas Rio Grande Valley where he earned a Master's of Science in Engineering Management in December 2017. During his graduate career, he worked as a recruiter for the College of Engineering and Computer Science, where he travelled to the Valley communities and schools to present the engineering opportunities found at the university as well as the opportunities available by pursuing an engineering degree. He was also hired as a graduate engineer for Hinojosa Engineering, Inc. in 2016 where he works with civil and structural design, construction management, construction administration, and project management. He has publications in the field of artificial intelligence and construction management. Currently, Carlos resides at 2018 W 42 ½ Street, Mission, TX 78573.