Construction Site-Layout Optimization Considering Workers' Behaviors Around Site Obstacles, Using Agent-Based Simulation

By

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

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First and foremost, I thank God for giving me the knowledge, strength, and ability to complete this work.

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Dedication

To my father, Saleh, my mother, Aljawharah, my stepmother, Muneerah, my grandfather, Abdulaziz, and my grandmother, Norah

Who

Have dedicated their lives to me

Abstract

The majority of construction projects, especially large ones, experience time delays, cost overruns, productivity loss, and/or accidents. This is particularly so in case of congested and disorganized sites that contain obstacles that affect workers' productivity and safety. Effective site layout planning, therefore, is one of the most important project management tasks, and has a significant impact on all aspects of construction, including safety, productivity, site operations, and ultimately time and cost. Site layout planning is a complex process that determines the best location for the needed site facilities (e.g., workshops, storage areas, equipment, etc.) needed to execute the project, so that productivity and safety are optimized. Despite the many simulation and optimization models in the literature for site layout planning, they mostly consider the site location without the low-level details of the workers' movements within site, particularly around site obstacles.

This research aims at developing a construction site-layout planning framework that uses Agent-Based Modelling and Simulation (ABMS) technology to perform a micro-level analysis of workers' movements and behaviors on site, to study the impact on site productivity and safety. For practicality, this research considers variety of productivity-hindering and safety-hindering obstacles on site. The model also considers two types of workers' behaviors in their movement around site obstacles: avoider, and aggressive. Given any site layout with any number of resources of different behaviors, the ABMS simulation quantifies the site overall productivity and accident/injury potential. To optimize the site layout, the framework integrates an optimization procedure that determines the optimum site layout that maximizes productivity and safety. A sensitivity analysis is also incorporated to examine the impact of obstacle type and workers' behavioral characteristics. The results of two case studies prove that the framework is a valuable tool for analyzing and assessing site productivity and safety, and for providing decision support for project managers in establishing site regulations and rewards for positive workers' behaviors. This research is expected to help construction companies deliver projects with less time and cost, and help to reduce accidents on complex sites.

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Chapter 1

Introduction

1.1 General

The construction site environment is dynamic and complex, and all objects on site interact with each other in a complex and temporal-spatial manner (Su 2013; Yahya and Saka 2014). Effective site layout planning is one of the most important project management tasks, and it ensures the success of a construction project (Zolfagharian and Irizarry 2014). Without a comprehensive and effective plan that considers the expected work flow among all the facilities on site, the travel distances, the work schedule, and the number of workers on site, inefficient maneuvering of workers and material can occur on site and can lead to many site problems (Andayesh and Sadeghpour 2014b; Su 2013). Previous studies have shown that site layout planning has a significant impact on all aspects of construction, such as scheduling, safety, productivity, cost, site operations, and time (Hegazy and Elbeltagi 2000; Kumar and Bansal 2014; Razavialavi, Abourizk, and Alanjari 2014). In the US, fatalities in the construction industry represent more than one third (36%) of all workplace fatalities (Zhang et al. 2015). In 2014, the Association of Workers' Compensation Boards of Canada statistics show that 919 workers died on the job and 25% of fatalities occurred in the construction sector (Silliker 2016). Sanders et al. (1989) reported that congested workspaces can cause up to 65% of efficiency losses and up to 58% of efficiency losses due to restricted access. Another research study at University

College London (UCL) reported that productivity loss is highly linked to poor site planning and conflict between subcontractors, and that poor site logistics can cause up to 20% of construction accidents (Tawfik and Fernando 2001).

Site layout planning is the process of determining the required facilities (i.e., workshops, storage areas, equipment, etc.) needed to execute the project and their optimal locations both geographically and time-wise throughout the project so that workflow on-site is optimized (Abdel-Fattah 2013). It is a process that starts before construction (i.e., the pre-construction stage) and carries on throughout the construction stage. Because construction projects involve many cyclic operations (e.g., earthmoving work) that involve uncertain durations and many resource interaction, researchers used simulation technology to model construction site layouts, and assess site productivity and safety (Su 2013).

Modeling of site layout is a very complex process that involves a large number of variables such as site size, required temporary facilities, required resources for the different tasks, and project scheduling (Kumar and Bansal 2014). Figure 1.1 shows a list of important variables that effect site layout planning. Each project has its own unique variables and requires a unique site layout plan (Zolfagharian and Irizarry 2014). While many site simulation efforts provide innovative approaches to assess site productivity and safety, only few efforts work at the lower level to model the workers and their behaviors, particularly around construction obstacles. Such a low level analysis is important to help the project manager establish polices that improve site productivity and safety.

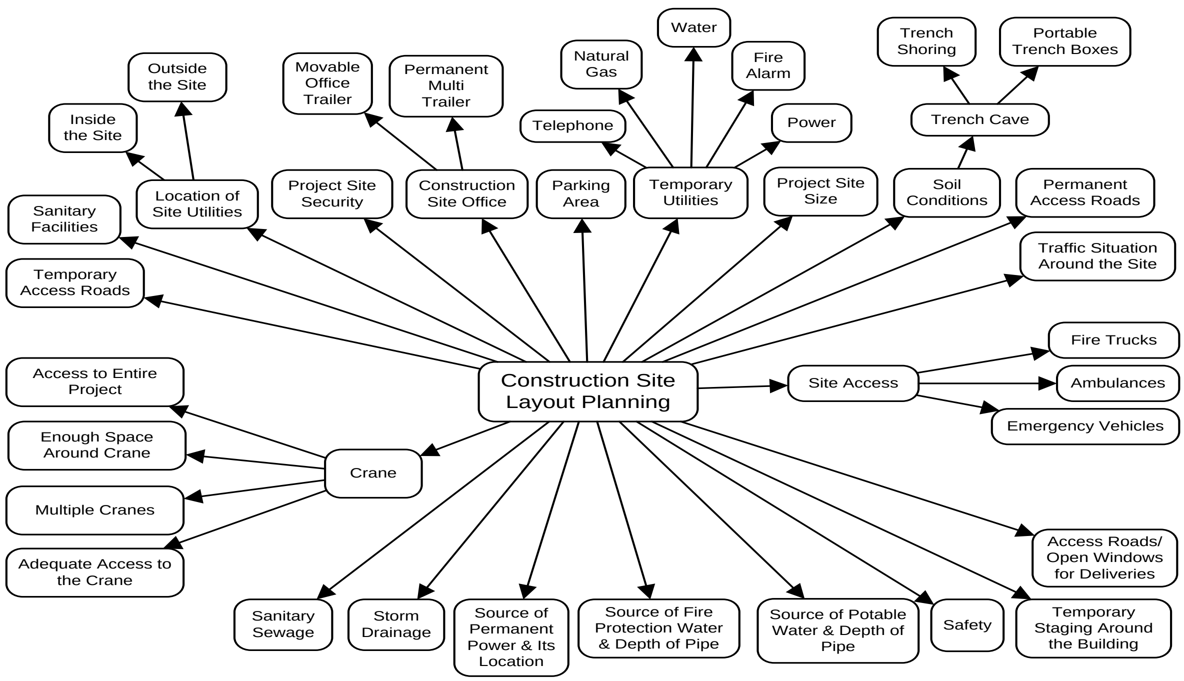


Figure 1.1: List of Site Layout Planning Variables (Zolfagharian and Irizarry 2014)

1.2 Research Motivation

This research aims at developing a construction site layout planning framework that is capable of micro-level analysis of workers' behaviors around site obstacles to enable accurate construction site layout optimization. The proposed system combines an optimization methodology for optimizing site layouts with an agent-based simulation technique that simulates the detailed flows of personal, equipment, and materials around site facilities and obstacles. The research has been motivated by the following:

1.2.1 Need for Efficient Site Layout Planning

Site-layout planning is one of the most important construction tasks, and has a direct influence on project success (Su 2013). Efficient layout plan can reduce cost, duration, and workspace conflicts and improve productivity, safety, and quality (Hegazy and Elbeltagi 2000; Kumar and Bansal 2014). Despite its importance, practitioners often ignore site layout planning, believing that it should be performed by site engineers while the project progresses, and the layout is often designed subjectively based on the planner's experience, codes of practice, trial and error, and previous similar projects (Kumar and Bansal 2015; Sjøbakk and Skjelstad 2015). However, this might result in safety problems, productivity losses, longer duration, higher cost, and space shortages (He and Wu 2012; Razavialavi et al. 2014). In addition, this method does not address the operating performance and uncertainty issues before construction, which leaves no time for corrective measures (Pang 2007).

1.2.2 Site-Layout Complexity and Lack of Low-Level Analysis

Construction site layout problems are characterized by being large in size, complex, involving a large number of interrelated factors, and having a very large number of possible solutions to choose from (Abdel-Fattah 2013; Kumar and Bansal 2015). For instance, a seemingly simple problem of allocating 10 facilities has well over 3,628,000 possible alternatives, and in reality, a project that requires 15 facilities is considered small (Yeh 1995). Therefore, using computers to assist in modeling and solving site layout planning problems is considered a necessity (Hegazy and Ersahin

2001). Despite the many optimization models in the literature, most models address the site layout planning problem from a macro perspective. The simplest types of model address a situation where a predefined list of temporary facilities is allocated among a list of predefined locations on site, considering only the preferences of having a given two facilities close to or far from each other. Other, more complex models consider any position on site as a potential location and can roughly consider the estimated total workflow between any two facilities. Very few models, however, have studied the detailed movement of workers at the micro level in order to study productivity and safety issues in a simulation-based environment (Khalafallah 2006; Kumar and Bansal 2015), nor have they examined the situations of workers individually or all workers together as a group. The results of the existing models, therefore, are simplistic and cannot estimate problems beforehand or suggest good corrective actions. Few models in the literature, for example, have considered uncertainty factors in site layout planning (Taillandier and Taillandier 2014; Ward and Chapman 2003).

1.2.3 Potential of Agent-Based Modeling and Simulation (ABMS)

With its basis in game theory, many researchers consider agent-based modeling and simulation (ABMS) as a new and better way of scientific discovery and experimentation (Chan, Son, and Macal 2010; Macal and North 2009). The most important feature of ABMS is its ability to simulate the interactions of agents (e.g., the workers and equipment that move on-site). This feature allows the simulation of the cascading effects of minor individual interactions, determining and examining tipping points, and understanding the causes and circumstances of emergent behaviors. Accordingly, mechanisms for improving a system by encouraging beneficial behaviors and discouraging malicious ones can be designed and presented. ABMS is recognized as among the most promising methods for simulating the behavior of individuals and has been proposed for modelling supply chain and infrastructure management (Bernhardt and McNeil 2008; Chen et al. 2013). However, only few efforts (e.g., Hammad et al. 2012; Vahdatikhaki et al. 2017) have used this promising technique for site layout planning. Several available AMBS platforms provide powerful simulation capabilities that can visualize all ongoing processes at any given point in time.

Site layout planning problems involve many interactions in the flow of workers, equipment, and material, which have a great impact on productivity and safety. Considering these interactions is important for the validity and practicality of site layout plans (Alanjari, RazaviAlavi, and AbouRizk 2015). ABMS is a practical technique that has a good potential for simulating low-level interactions and behaviors on site.

1.3 Research Objectives and Scope

The primary objective of this research is to develop a construction site layout planning framework that combines a site-layout optimization procedure with an ABMS model for micro-level simulation of construction site operations, considering workers' behaviors around site obstacles. The principal objectives are as follows:

1. Study the construction site layout planning process and existing optimization methods, understand the interactions between objects on site, the types of site obstacles, and different workers' behaviors on site;
2. Develop an Agent-Based Modeling and Simulation (ABMS) framework that considers the sizes and locations of site facilities and obstacles, and other parameters that affect the flow of workers, materials, and equipment on site. The framework involves efficient representation of the agents, and their autonomous movements and behaviors around obstacles. Accordingly, it assesses site productivity and accident potential;
3. Develop a site layout optimization model that interacts with the ABMS simulation model to determine the optimum location of all temporary facilities, to maximize productivity and minimize accident potential; and
4. Implement the proposed framework on a computerised decision support system and verify the framework using both hypothetical and actual project cases.

This research applies to planning site layouts at the pre-construction and construction stages of projects, where practitioners need to optimize the construction site layouts and establish site guidelines to promote positive workers' behaviors. The research attempts to establish an automated simulation-based site layout analysis tool, and also provides a visual representation of construction processes to determine better productivity and safety improvement measures.

1.4 Research Methodology

The proposed research methodology is shown in Figure 1.2, and is as follows:

a. Conduct a comprehensive survey of the literature to investigate current site layout planning and simulation methods. Analyze the site layout planning process, identify its problems, and list the solutions from the literature.

b. Investigate and determine the influencing factors and the uncertainty sources related to site layout planning.

c. Examine site boundary conditions.

d. Mimic the natural behavior of agents and work flow and examine their behavior within the facilities and between work locations.

e. Develop an agent-based model on the NetLogo platform for simulating and visualizing construction processes.

f. Develop a genetic algorithm optimization procedure for optimizing the locations of temporary facilities.

g. Create a prototype framework that combines the optimization and simulation models.

h. Collect data from actual construction project case studies.

i. Apply the prototype system to practical case studies for verification.

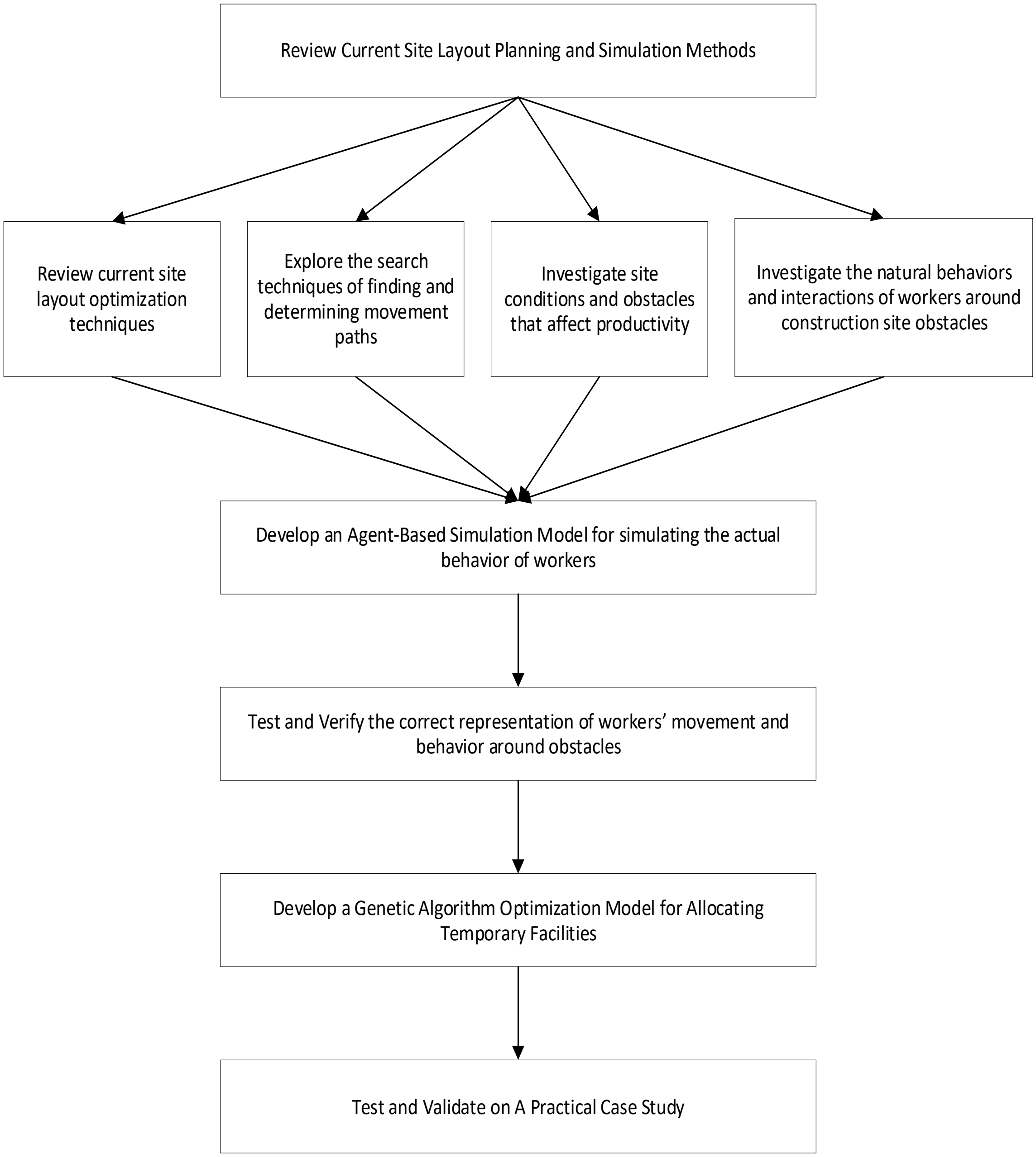


Figure 1.2. Schematic Diagram for Research Methodology

1.5 Thesis Organization

This research proposes a framework that combines an ABMS simulation GA optimization models for construction site layout planning. It comprises six chapters:

Chapter 2: presents the literature review related to construction site layout planning definitions, problems, challenges, and influencing factors. Then, it discusses the challenges of modelling site layout planning problems including special representation, constraints, and uncertainties. After that, it reviews the current research efforts related to site layout planning tools focusing on knowledge-based systems, optimization techniques, and simulation methodologies.

Chapter 3: introduces the proposed ABMS simulation and GA optimization framework for site layout planning. It discusses the development of the ABMS simulation model and provides details about its main components: inputs, agents' behaviors and self-determined paths, simulation and analysis, and outputs. Then, an illustrative application on an example case study is presented.

Chapter 4: introduces the Peter George Centre for Living and Learning case study. It then presents the implementation of the ABMS simulation model on the earthmoving phase of the project. Alternative on site trucks' rout and exit is then examined and compared with the case project data.

Chapter 5: provides the implementation of the proposed framework on the construction phase of the case project. Then, it presents the GA optimization settings including parameter values, objective function, and reproduction mechanism. After that, a sensitivity analysis on the sizes and shapes of site obstacles is discussed. Based on the analysis results, recommendation on how to deal with site obstacles is provided

Chapter 6: discusses the research conclusions, contributions, and the future research work.

Chapter 2

Literature Review

2.1 Introduction

This chapter reviews and discusses the literature body of knowledge related to the site layout planning and the efforts to optimize site layouts. It begins with exploring the problems associated with modeling construction site layout. Then, it introduces the different approaches developed to address the site-layout planning problem. After that, it focuses on discussing the importance and potential of simulation in the domain of site layout planning. Then, it reviews the path planning approaches used in the modeling of moving objects. The last part, presents an overview of the current research on workers' safe behavior on construction sites.

2.2 Modeling the Construction Site Layout

In practice, site layout planning is primarily a subjective process that relies on the expertise and knowledge of construction managers and/or site planners (He and Wu 2012). However, this subjective process might result in productivity loss, safety problems, space shortages, longer duration and higher cost (He and Wu 2012; Razavialavi et al. 2014). In addition, the operating performance and safety issues are usually not addressed before construction, leaving no time for corrective measures (Pang 2007).

During the past few decades, considerable research on site layout planning using simulations has been conducted (Razavialavi and AbouRizk 2013; Razavialavi et al. 2014). The main research directions in modeling site layout problems can be classified as: static, discrete, or continuous. Static layout modeling does not consider time or interactions between resources, and the output is a single plan for the whole duration of the project (El-Rayes and Said 2009). Due to the dynamic and complex nature of construction projects, static plans will eventually fail to meet site requirements at a certain time, and thus are not suitable for simulating and representing site layout planning problems (El-Rayes and Said 2009). In contrast, continuous models produce a plan that continuously changes over time. However, construction tasks have a discrete nature that makes them best-suited by discrete event time representations.

The challenges in construction site layout lie in the process of allocating land and facilities while satisfying layout objectives and constraints, maximizing safety, and minimizing project cost and duration (Elbeltagi, Hegazy, and Eldosouky 2004). Due to the large number of planning variables, types of facility, and large solution search space involved in site layout, computer modeling and simulation is considered a very useful approach in dealing with such challenges (Abdel-Fattah 2013), a list of permanent and temporary facilities is shown in Table 2.1.

Over the years, many research projects have been developed to computerize and automate site layout planning. Modeling site layout planning, however, still poses many challenges (AbouRizk 2010) in terms of site layout spatial representation; and the representation of work constraints. The most widely used techniques for modeling space in site layout planning are grid representation, reading spatial data

Table 2.1. Permanent and Temporary Facilities

Permanent Facilities	Temporary Facilities						
	Workshops	Storage	Labor Residences	Services	Safety and Security	Utilities	Equipment
Constructed Building	Carpentry Workshop	Rebar Storage	Labor Rest Areas	Laydown Area	First Aid Office(s)	Light and Power	Cranes
Water Supply Piping	Equipment Maintenance Shop	Scaffolding Storage	Labor Dormitories	Access Roads	Fire Alarms	Propane Tank	Scaffolding
Fencing	Batch Plant and Precast Concrete Shop	Steel Storage	Engineers/Staff Dormitory	Field Offices and Sheds	Access for Fire Trucks, Ambulance, and Emergency Vehicles	Water Supply	Construction Elevator or Dumbwaiter
Power Cables	Metal Fabrication and Electrical Shops	Spoil Pile	Site Parking	Construction Stairs	Fire Protection Equipment	Telephone	Temperature and Moisture Control
Sewer	Sampling Lab	Oil Depot	Hoarding	Subcontractors’ Offices	Enclosures and Barriers	Sanitary Facilities	Compressor Station
Drainage	Rebar Fabrication Yard	Explosives Storage		Drainage and Pumping Systems	Doorways	Heating	
Natural Gas Piping	Equipment and Tool Sheds	Storage for Waste Material, Rubbish, and Debris		Erosion and Sedimentation Control Measures	Information and Guard Offices	Sewers	
	Formwork Shop	Cement, Sand, and Aggregate Storage		Machine Room(s)		Ventilation	
	Welding Shop	Equipment Storage		Retaining Walls		Dewatering	

from CAD drawings, and exporting site information from a BIM model. In grid representation, the available site and facilities areas are divided into a grid of equal units (see Figure 2.1). This will simplify the modeling of space representation and utilization. This technique was used by Elbeltagi et al. (2004) and Mawdesley et al. (2002). In the second technique, site spatial information is exported from CAD drawings to the simulation model. An example of a research project using this technique is Sadeghpour (2004). In the third technique, the simulation model reads site and facility geometry data from a BIM model. Cheng and Kumar (2014) and Astour and Franz (2014) adopted this technique for their research. From a practical viewpoint, grid representation does not accurately represent non-rectangular components, which can result in overlapping in the site plan.

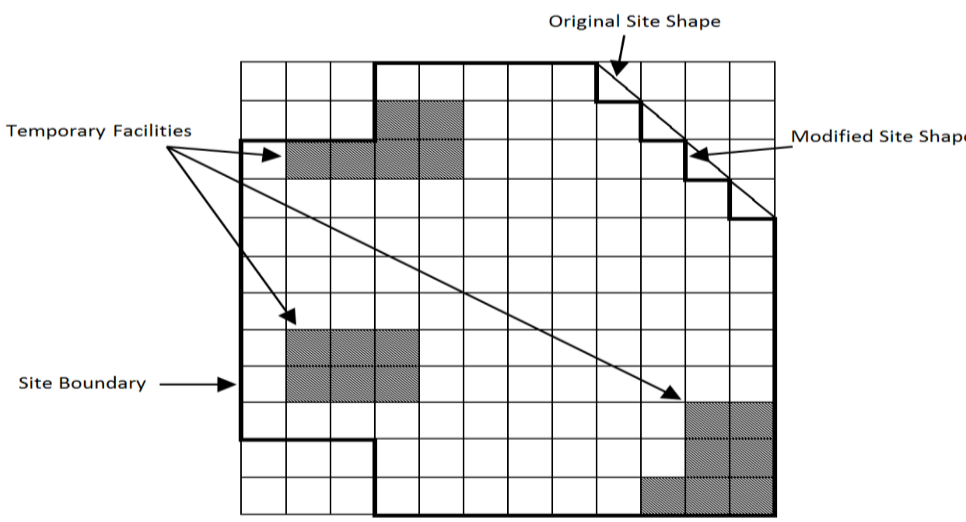


Figure 2.1: Site Grid Representation

Designing a site plan is the process of allocating temporary facilities to allow them to function efficiently while considering many constraints related to safety, site conditions, site geometry, facility geometry, cost, and work schedule (Sanad, Ammar, and Ibrahim 2008). Accidents and injuries on construction sites have been viewed as major constraints to be avoided (Elbeltagi et al. 2004). Constraints guide the model to better achieve its intended goal. Inappropriate setting of constraints may over- or under-specify the problem, leading to modeling problems and/or low quality outputs (Abdel-Fattah 2013).

2.3 Construction Site-Layout Planning Models

Over the last few decades, different approaches have been developed to model construction site layout problems, and the following subsections will present these approaches in detail.

2.3.1 Knowledge-based Systems

Knowledge-based (KB) systems can be defined as computer programs that use expert knowledge and heuristic strategies to solve problems that require considerable expertise and judgment (Chau and Anson 2002). The main advantage of KB systems is that they can help in addressing problems where no algorithmic solutions exist (Sadeghpour 2004). The performance of such systems is directly influenced by the methods of modeling and representing expert knowledge. “Expert” systems are considered KB systems in which human experts’ ability to solve problems is simulated (Ignizio 1991).

During the last few decades, several expert systems have been developed to help in facility layout planning problems. CONSITE (Hamiani 1987) is one of the earliest expert systems developed to help in construction site layout problems. It allocates facilities by using rules and priorities given to the facilities by experts based on the frequency of trips between a given facility and the work area. SITEPLAN is a knowledge-based system developed in (Tommelein et al. 1991) for laying out temporary facilities on construction sites. The inputs for this system include permanent facilities, dimensions of temporary facilities, access roads, and location constraints. SITEPLAN represents facilities as two-dimensional rectangles. However, neither CONSITE nor SITEPLAN support space reusability over time. In a continuation study of SITEPLAN, MOVEPLAN (Tommelein and Zouein 1993) was developed to support dynamic facility layout. MOVEPLAN does not generate site layout plans, however, and the user is responsible for generating a sequence of layouts covering all layout changes through the duration of the project. MOVEPLAN works as a decision support tool that verifies the consistency of the layouts generated by the user with the schedule and with each other.

Zolfagharian and Irizarry (2014) developed a rule-based checking system that reviews construction site layout designs. The system evaluates the designs against predefined rules to ensure minimal conflicts in situations such as worker circulation, security, and lighting. The rule-based system checks site layout designs in BIM-3D models and suggests solutions according to predefined rules. In the first step, the design rules are interpreted from a human language format to a machine-processable format using the Industry Foundation Classes (IFC). Then, the user incorporates the site layout designs into the BIM model. After that, the system evaluates the BIM model against the design rules. Finally, it generates a report including results as well as solutions to improve the designs. If the design rules are satisfied, the system results pass; otherwise, the site design fails.

2.3.2 Optimization Techniques

Optimization techniques can be classified as either traditional or evolutionary based on their algorithms. Traditional optimization algorithms such as integer, linear, or dynamic programming are mathematical methods for finding the optimum solution (Moselhi and Lorterapong 1993), but these algorithms cannot solve large-scale or complex problems such as site layout planning problems (Hegazy and Kassab 2003). On the other hand, evolutionary optimization techniques such as Genetic algorithms (GA) have the ability to deal with and solve large-scale problems. Genetic Algorithms simulate natural evolutionary processes such as “survival of the fittest” by using simple formulations to reach an optimum or near-optimum solution (Lam, Tang, and Lee 2005).

GA is the most widely used method for solving site layout planning problems, and is very effective (Abdel-Fattah 2013). It can be described as a type of machine-learning technique that searches for optimal solutions in an intelligent way to find the best solution (AL-Tabtabai and Alex 1999). GA is more suitable for solving problems that are relatively large, have no adequate mathematical solutions, and when a near-optimum solution can be acceptable (AL-Tabtabai and Alex 1999). GA starts by randomly initiating a population of possible solutions according to the nature of the problem and the underlying formulation. Then, reproduction operators (crossover and mutation) generate a new sample population of potential optimum solutions (Whitley 1994). Each candidate solution is evaluated using a fitness function that determines its optimality. The formulation of GA depends on the nature of the problem and algorithm's goal; hence, each problem has its own unique formulation. Different GA formulations for different site layout planning applications are presented in Table 2.2.

Table 2.2. Genetic Algorithm Formulations for Different Layout Planning Applications

Authors (year)	Application	Fitness Function	Remark
Pham and Onder (1992)	Workplace Design	$\frac{1}{2}\sum_{i=0}^{n}\sum_{j=0}^{n} W_{ij}d_{ij}$	d = distance between components W = weighting coefficient expressing the importance among the components
Kochhar et al. (1998)	Facility Layout Problem (Industrial)	$\sum_{i=1}^{n}\sum_{j=1}^{n} f_{ij}d_{ij}$	f = volume of flow between departments d = distance between the two departments
Hegazy and Elbeltagi (1999)	Site Layout Problem	$\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}R_{ij}$	R_{ij} = desired proximity weight value between facilities d = distance between facilities
Tam et al. (2001)	Supply Locations Around Tower Crane	$\sum_{j}^{n}\sum_{k}^{n} TQ_{jk}C_{jk}$	T = hook travel time Q = quantity of material flow C = cost of material flow per unit quantity and unit time
Wong, Fung, and Tam (2010)	Site Precast Yard Layout	$\sum_{k=1}^{n}\sum_{i=1}^{q}\sum_{j=1}^{q} TCL_{Mkij}$	TCL =total cost of resource Mk flow between locations i and j.
Abotaleb, Nassar, and Hosny (2016)	Site Layout Problem (Building Project)	$\sum_{i=2}^{n}\sum_{j=i-1}^{n-1} D_{ij}W_{ij} + P_c + P_s + P_a + P_{bz} + \sum_{i=1}^{n} RC_i$	D_{ij} =distance between facilities i and j. W_{ij} =desired proximity weight value between facilities i and j. P_c =collision penalty P_s =out-of-site Penalty P_z =area penalty P_{bz} =buffer zones penalty RC_i =relocation cost of facility i from phase a to phase a-1
Panagiotis M and Athanasios P (2018)	Site Layout Problem (Multiple Project Types)	$w_1f_1 + w_2f_2$	f_1 =total cost f_2 =equivalent safety and environment decision component (bonuses/penalties) w_1 =weight coefficients related to f_1 w_2 =weight coefficients related to f_2

Elbeltagi et al. (2004) developed a spreadsheet-based optimization model for maximizing productivity and safety where productivity is maximized by minimizing travel distances on-site, and safety is incorporated using closeness relationship weights assigned to the temporary facilities, reflecting the planner's operational and safety preferences. The closeness relationship weights can have positive or negative values. Positive values reflect a need for closeness between two facilities, and negative values mean that they need to be far away from each other. The proposed model was implemented on the real construction case of the Tanta University Educational Hospital.

Said and El-Rayes (2010) proposed a framework for optimizing site layout and site security for critical infrastructure projects. The model uses GA to minimize overall site cost and security risks, and generates a dynamic site layout plan for the entire project duration. The site plan is optimized by minimizing travel and security costs, while security risks are minimized by optimizing the site lighting system. Then, the impact of implementing the optimized site plan on the security system is quantified using some metric measures. The framework was tested using an example project.

2.3.3 Simulation Efforts

Simulation is a computer-based imitation of a construction process or system over time in order to understand its underlying behavior. A key power of simulation is its effectiveness in designing and analyzing complex construction processes under different conditions. Simulation enables addressing the dynamic and uncertain issues and comparing various alternatives without affecting the real system. The outputs of a simulation model provide insights into a system for evaluating its performance and aiding in the decision-making process (AbouRizk 2010; Pang 2007).

There are three major approaches in construction simulation modeling: System Dynamics (SD), Discrete-Event Simulation (DES), and Agent-based Modeling and Simulation (ABMS). An overall comparison of the characteristics of the three approaches is presented in Table 2.3. The table uses a simple "amusement park" example to illustrate the differences among these simulation methods. As indicated by Table 2.3, System Dynamics suits policy analysis and strategic decision-making (Forrester 1961; Sterman 2000), and thus, will not be discussed. Due to the discrete nature of construction processes, DES is dominant in the area of construction site-layout planning (Pang 2007). On the other hand, while ABMS is a relatively new approach (Macal and North 2010), it is recognized as being among the most promising method for analyzing construction problems (Bernhardt and McNeil 2008; Chen et al. 2013). In the following sections, DES and ABMS are discussed in detail.

Table 2.3. Comparison among different simulation Approaches (Based on Rashedi and Hegazy 2016)

	System Dynamics (SD)	**Discreet Event Simulation (DES)**	**Agent-Based Simulation (ABMS)**
Decision-Making Level	Strategic	Tactical/Operational	Operational
Type of Applications	Policy Investigation	Production Analysis, etc.	Consumer Behavior, etc.
Sample Software	Vensim, Stella	Simul8, Arena	AnyLogic, NetLogo
Limitation	Limited to holistic analysis	Human behavior is not taken into account	Focus on the behavior of entities (agents, or humans)
Example Decisions (Amusement Park)	Pricing strategies, discounts, future investments, etc.	Analysis of ride time, waiting time, service time, etc.	Analysis of each user (agent) in terms of satisfaction and behavioral pattern.

a. Discrete-Event Simulation

DES is a widely used analytical tool for replicating the performance of a system under various conditions, providing decision-makers an insight into the system, and is the dominant technique used in simulating construction operations (AbouRizk 2010). It can be generally defined as a technique for modeling the evolution of a system over time. DES models require accurate historical data or estimates of future performance to efficiently simulate a system's performance. This technique is suitable for simulating systems that change at specific points in time, such as production lines and customer or resource arrival rates. In DES, an event is determined by state changes and can be either time-driven or event-driven (Lu 2003; Sweetser 1999). There are many commercial tools that support DES modeling (Borshchev and Filippov 2004), and most of these tools include animation capabilities for visualizing the simulated system, which is a valuable feature for increasing the understanding of the system (Greasley 2009; Sweetser 1999).

From a construction viewpoint, DES is a technique that uses operations data and statistics to predict the state and performance of a future construction process (Lu 2003). DES models are classified, based on their underlying modeling strategy and perspective for viewing a real system, into three classes: process interaction (PI), activity scanning (AS), and event scheduling (ES). The PI strategy places emphasis on the entities flowing in the system which perform specific activities. In AS, the emphasis is on the activities and the identification of the conditions of their occurrence. ES is a strategy that is often combined with AS or PI as an accessory for enhancement (Martinez and G.Ioanou 1999).

For simulating construction site layout planning problems, DES has certain limitations and drawbacks. For instance, humans in DES can only be modeled as resources, and the effect of their behavior on the performance of the system cannot be captured (Greasley 2009). Incorporating human behavior gives a better opportunity to understand site layout planning problems and provides a more realistic representation of the real process. Entities in DES models are simple, reactive, and rely on a central mechanism for their actions and decisions, which limits the technique's ability to simulate real entities that are proactive and independent (Chan et al. 2010). Moreover, DES is best suited for simulating systems involving cyclic and linear processes (Lu et al. 2007; Zhou, AbouRizk, and Al-Battaineh 2009). Site layout planning problems do not involve such processes, and hence this technique will produce an incomplete replication of the real process. Therefore, most of the previous efforts to use DES for simulating construction site layout have tended to simplify the site layout representation (Zhou et al. 2009).

Many DES applications and models have been developed for simulating construction site layout planning. Rahman and Carmenate (2015) constructed a DES model to identify and assess dangerous hotspots (e.g., sites where collisions between workers and machinery may occur) in an example case study of excavation and concreting activities. Zhou et al. (2009) developed a DES model and integrated it with a genetic algorithm to optimize and validate site layout planning for a tunneling project. Lu (2003) developed a simplified discrete-event simulation approach (SDESA) for spotting bottlenecks in a construction site and applied it with the critical path method (CPM) in simulating a road construction project. Then, Lu et al. (2007) enhanced the SDESA by making it more generic, and validated the model by simulating two case studies, one on earth-moving operations and another on concreting operations . Wimmer et al. (2012) coupled a DES model with a mathematical optimization procedure to minimize transportation equipment travel times in earthworks construction processes.

b. Agent-based Modeling and Simulation

ABMS is a new approach to modeling complex systems comprising interacting, autonomous agents. Over the past 10 years, ABMS has gained increasing attention across a variety of application domains such as supply chains, social networks, biology, crowd management, material science, chemistry, archaeology, and many others. Some consider ABMS a new way of treating science and may surpass traditional inductive and deductive reasoning as discovery methods (Chan et al. 2010; Macal and North 2009).

There is no universal agreement on the definition of ABMS (Chan et al. 2010). However, it can be generally defined as simulation systems with agents, entities, or objects that repeatedly interact with each other and their environment in an autonomous way (Chen et al. 2013). The most important feature of ABMS systems is that they are built from the ground up by modeling the agents' behaviors and interactions that form the overall behavior of the system. Agents' behaviors and interactions are described by a set of rules that range from simple if-then rules to complex behavioral rule-sets (Macal and North 2009).

In the context of ABMS, agents are proactive, heterogeneous, dynamic, and autonomous. There is no agreement on the precise definition of the term "agent", however, some require independency for a component to be called an agent and others insist that it also must be adaptive. However, a component can be called an agent when it acquires certain essential properties (Chan et al. 2010; Macal and North 2009, 2010; Wooldridge and Jennings 1994):

- **Autonomy:** This is considered when an agent can operate independently and have some self-control over its own actions as well as interactions with other agents and the environment.
- **Proactive:** This is considered when an agent has its own initiative and is able to exhibit goal-directed actions, and does not simply react to the environment.
- **Social:** This is considered when an agent has interactions with other agents and with the environment that influence its behavior and decisions.
- **Self-contained (Modular):** This is considered when an agent is identifiable through unique attributes that allow it to be distinguished from and recognized by other agents.

ABMS is different from other simulation techniques (Chen et al. 2013). For instance, ABMS attempts to simulate possible individual behavior, which is totally different from traditional operations research (OR) methods that seek to find the optimal behavior (Macal and North 2009). The heterogeneity of agents and the system's overall emergent behavior are the distinguishing features of ABMS compared to DES and SD (Macal and North 2010). Another important difference between ABMS and DES is in the nature of agents. The agents in ABMS are proactive and have the ability to initiate actions, communicate, and make decisions, while in DES, agents are reactive and rely on some central mechanism that controls their actions and decisions (Chan et al. 2010). In contrast with other simulation techniques, ABMS models are built from the bottom up by modeling agents' behaviors and interactions, which generates the behavior of the overall model (Klügl and Bazzan 2012).

ABMS offers several advantages over other simulation techniques. It is more powerful and wide-ranging, as it is capable of capturing more complex dynamics and structures (Borshchev and Filippov 2004). ABMS captures emergent behavior and facilitates a more natural representation of real systems (Bonabeau 2002). Building ABMS models does not require mathematical sophistication, and this is due to the object-oriented and distributed nature of this approach (Chen et al. 2013). Another advantage of ABMS is its ability to simulate the actions and interactions of the agents, which provides better opportunities to understand their nature and the system as a whole. ABMS models are more capable of handling and simulating the complexity of real systems, which often involve a large number of interacting, autonomous, and proactive agents (Chan et al. 2010). The ground-up modeling in ABMS creates better opportunities to understand the causes and circumstances of the occurrence of the agents' interactions and the system's behavior (Klügl and Bazzan 2012).

Compared to other simulation techniques, ABMS is the most suitable for simulating site layout planning problems, as it is much more capable of capturing and modeling the interactions and dependencies involved in such problems (Borshchev and Filippov 2004). The flows of equipment, workers, and materials on site involve many interactions between each other and with the environment (space), and have both dependent and independent properties that can greatly affect the layout planning process. Analysing and understanding these flows facilitates the understanding and determination of the causes of conflicts, accidents, and productivity loss, and accordingly, in developing a plan that reduces or eliminates them (Chen et al. 2013). Using simulation for examining different scenarios and alternatives by trying various plans and behavioral rules is a very useful process for analysing and preparing for the uncertainties associated with construction (Ward and Chapman 2003). ABMS models can be easily modified to perform such analysis even with little available information (Borshchev and Filippov 2004).

Although the use of ABMS in site layout planning has great potential as a management tool, a very limited number of applications currently exist in this area, so the capabilities of ABMS have not been fully explored and utilized in site layout planning. Among the limited research efforts, Jabri and Zayed (2017) developed a model named Agent-Based Simulator for Earthmoving Operations (ABMSEMO) using the modeling tool AnyLogic 7. The model considers four types of agents: bulldozers, loaders, haulers (trucks) and dump spotters. The model was implemented on a real case of a riverbed soil excavation. The outputs were compared with the outputs of an EZStrobe DES model for verifying the quantitative aspects of the ABMS model.

Astour and Franz (2014) used ABMS for evaluating the utilization of construction equipment and labor. They developed a two-phase system for optimizing and evaluating site layout plans. In the first phase, a BIM-based optimization model generates a site layout plan with the optimal or near-optimal size and location of facilities, considering the buildings and obstacles at the site, equipment, number of staff, construction methods, and safety measures. The second phase is an agent-based model that simulates the optimized plan to evaluate the interaction of equipment with the environment and material flow, taking into consideration the possible collisions. The output of the simulation model provides the degree of utilization of site equipment and its operators. The output data of the BIM model have to be manually put into the simulation model, and the agent-based simulation is modeled in the “SeSAm” (Shell for Simulated Agent Systems) environment.

Pradhananga and Teizer (2014) developed an agent-based model in MATLAB for simulating earthmoving operations where real-time data for a real project were used to analyze site traffic congestion. The model simulates the movement of trucks starting at the time they enter the site, and continues through their loading and exiting the site. The output is a congestion index (CI), which is the ratio of the number of truck movements to the actual number of attempts to move. The number of trucks was increased to estimate the maximum number of loads that the excavators can provide.

Taillandier and Taillandier (2014) developed an ABMS model for assessing the impact of risks (high rates of work, low security levels, work accidents, errors in design, etc.) on construction projects. The model is called SMACC (Stochastic Multi-Agent simulation for Construction projeCt). SMACC is modeled on the GAMA open-source agent-based simulation platform. The model simulates an entire project, considering potential risks and assessing their impact on cost, duration, and quality. A real construction project for a nursing training institute in southwestern France was implemented using three different strategies. The first strategy was what is usually chosen for a real project. The second aimed to improve safety by training and special monitoring, which implied more time for some tasks. In the third strategy, quality requirements and budget were increased for every task. The results showed that each strategy achieved its goal. The first showed average results that were close to the actual project data. The second produced the worst quality and highest cost, but the shortest duration. The third strategy had the highest quality, cost equals to the cost of the second strategy, and duration equal to the duration of the first strategy.

Kim and Kim (2010) developed an ABMS system to evaluate the impact of equipment traffic flow on the efficiency of construction operations. The system was built to simulate truck traffic flow in the Busan New Port Construction Site Project, considering the interactions between trucks when they arrive simultaneously at an intersection. Simulations were performed with different combinations of equipment and different numbers of trucks, and the simulation results showed that additional equipment could decrease truck speed by 48.8% and work efficiency by 61.6%.

Watkins and Mukherjee (2009) created an ABMS model that represented workers and tasks as agents in order to study congestion and spatial interactions. The model was used to explore the impacts of individual and crew interactions on productivity and labor flow. The model simulated an sample case study of a wall construction project and involved several tasks and three crews, each comprising three skilled workers and two helpers. The model considered the sensitivity of construction activities to site congestion through a constant metric measure for each type of worker (c1, c2). Experiments were conducted to test the model against principles of work force management, and ten runs using different values of c1 and c2 for each experiment were performed. The first experiment used the original number of workers, and for the second one, at a certain time a skilled worker was removed from each crew. In the third, the second experiment was repeated by removing a skilled worker and a helper. The results confirmed the principles of construction, and also showed that site congestion can affect work productivity and vice versa.

All of these previous approaches focused on only one, or at most a few, aspects of site layout planning. It is important to simulate the whole construction process to capture the interactions between parties, which is essential to understanding the processes, causes, and circumstances of events and occurrence of problems. Moreover, these models used ABMS to only simulate some construction processes, without having agents with decision-making or problem-solving capabilities. This feature in most cases is important to realistically represent a real process, and it is within the capabilities of ABMS and one of its main characteristics. None of these models have tested and tried different behavioral rules or models. A small change in these rules can lead to new emergent behavior, which can give a deeper insight into the process under investigation.

2.4 Path Planning Approaches

The shortest-path is a well-studied problem in computer science, specifically in graph theory, with many applications using shortest-path algorithms (Madkour et al. 2017). These applications include construction planning, transportation systems, social networks, and computer games.

In construction, activities require different resources (labor, material, and equipment) that continuously move between different locations on site. To plan and optimize construction operations, it is required to identify the proper locations of site objects (e.g., facilities and obstacles) and the proper traveling paths on site. In the literature, several approaches have been used to determine the movement paths between two points. These approaches can be categorized into two categories: finding the shortest path; and finding the optimal path (Andayesh and Sadeghpour

2014a; Madkour et al. 2017; Rahman et al. 2016). Each category is discussed in detail in the following subsections.

2.4.1 Finding the Shortest Path (Distance)

Three approaches have been used in site layout planning to find the distance between two points: direct, grid based, and visibility graph (Andayesh and Sadeghpour 2014a). The main steps and assumptions of these approaches are as follows:

a. **Direct Approach:** The direct approach is the simplest one which uses the X-Y coordinates of the start and destination points to determine the distance between them. In this approach, the distance is extracted directly using two scenarios: Euclidean and rectilinear (e.g., Figure 2.2). The Euclidean distance is the straight line between two points. The rectilinear distance is the rectilinear line between two points. In both scenarios, the distance can be calculated as follows (Andayesh and Sadeghpour 2014a):

$$Euclidean\ Distance = \sqrt{(X_a - X_b)^2 + (Y_a - Y_b)^2} \tag{2.1}$$

$$Rectilinear\ Distance = |X_a - X_b| + |Y_a - Y_b| \tag{2.2}$$

where (X_a, Y_a) and (X_b, Y_b) are the coordinates of points a and b. Despite this approach's simplicity, it does not consider the detours required to be made around site objects (e.g., obstacles and facilities) to move from one point to another (Andayesh and Sadeghpour 2014a).

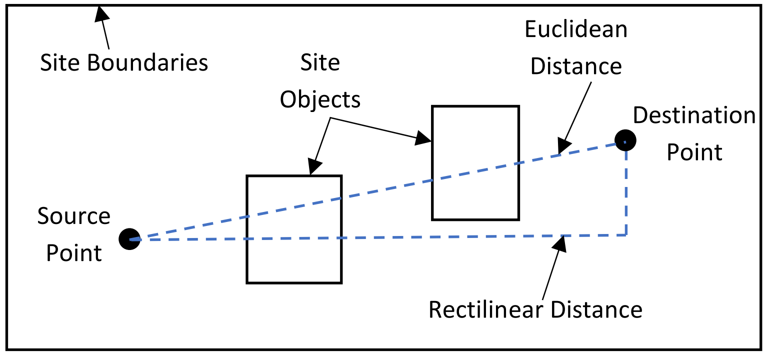


Figure 2.2. Direct Approach: Euclidean and Rectilinear Distances (Based on Andayesh and Sadeghpour 2014a)

b. **Grid-Based Approach:** To overcome the direct approach's limitation, this approach uses a grid based system to determine the distance between two points and considers detours around site objects (Soltani et al. 2003; Soltani and Fernando 2004). The site is represented by a graph of an orthogonal grid system where intersections represent the graph nodes and the arcs are the lines connecting adjacent nodes, Figure 2.3. This graph is then used to fine the shortest path which represents the distance between two points. The process of finding the shortest path starts by identifying the nodes based on the grid size and the site shape. Then, eliminating the nodes that fall within site objects. After that, creating the arcs by connecting the remaining adjacent nodes. Finally, searching for the shortest path between start and destination points (Andayesh and Sadeghpour 2014a). The accuracy of this approach can be increased by reducing the size of the grid units and/or by using more connecting arcs (connecting 8 adjacent nodes). However, this requires more computational effort and time.

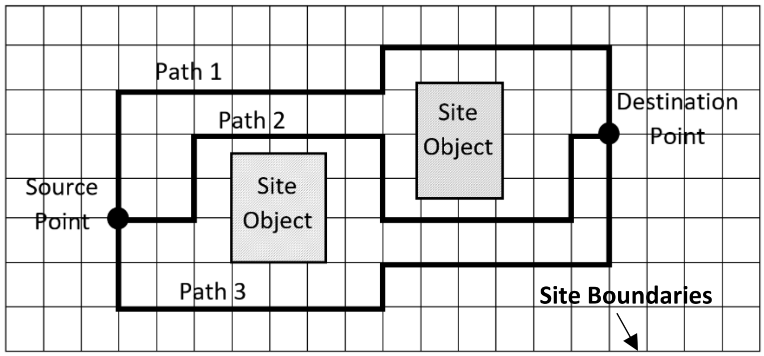


Figure 2.3. Grid-Based Approach (Based on Andayesh and Sadeghpour 2014a)

c. **Visibility Graph Approach:** This approach depicts more accurately the behavior of the moving resources on site and their maneuvering around site objects (e.g., facilities and obstacles). It creates a graph with all possible paths between two locations including detoured path around site objects. It starts by identifying the graph nodes which include the start and destination points and the objects' vertices (Figure 2.4b). Then, creating all possible arcs by connecting each two nodes that are visible to each other (Figure 2.4c). After that, eliminating the arcs that passes through the site objects. Finally, comparing the remaining arcs and choosing the shortest one (Figure 2.4d). However, this approach has been used in robotic path planning with a very limited applications in site layout planning

(Andayesh and Sadeghpour 2014a; de Berg et al. 1997; Bohács, Gyimesi, and Rózsa 2016).

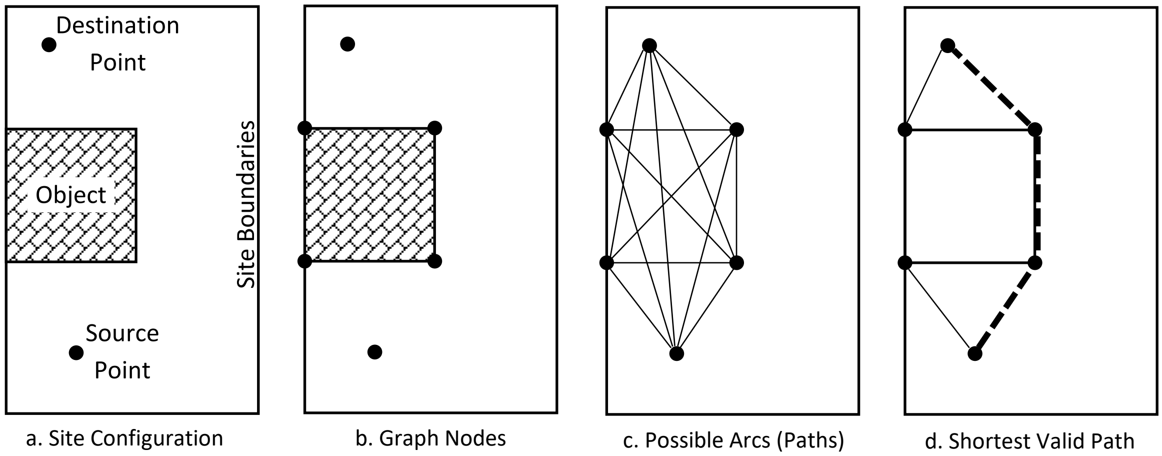


Figure 2.4. Visibility Graph Approach (Based on Andayesh and Sadeghpour 2014a)

2.4.2 Finding the Optimal Path

Path optimization algorithms operate over graphs with weights for the nodes (edges). The weights can represent various criteria such as distance, cost, or travel time. The choice of the algorithm type, weights, and other settings depends on the application and the characteristics of the graph (Madkour et al. 2017). The best suited optimization algorithms for construction site path planning are Dijkstra, A*, RRT* (Rapidly-explored Random Trees), and GA search algorithms (Bohács et al. 2016). These are briefly discussed as follows:

a. **Dijkstra Algorithm:** Dijkstra algorithm (Dijkstra 1959) is a single-source algorithm that starts from a source node and searches for the shortest-path to the destination by checking all other arcs (or edges) connected to the source node. The algorithm operates iteratively until all nodes are searched. An advantage of the algorithm is that it does need to search all arcs which saves processing time by not trying, for example, arcs with high weight values. However, it cannot deal with negative weight values and applies only to static graphs (Madkour et al. 2017).

b. **A* Algorithm:** A* (Hart, Nilsson, and Raphael 1968) is a goal-directed heuristic search algorithm that uses additional annotations to nodes or arcs of the graph that consist of additional information allowing it to determine and eliminate parts of the graph from the search space. Compare to other algorithms, A* uniquely takes into account and keeps track of the distance traveled (Madkour et al. 2017). This method uses heuristic functions to denote the cost of movement and describe distance to the destination point (Bohács et al. 2016). The strong points of A* algorithm is that it always finds the shortest-path and that it is faster than Dijkstra. On the downside, it requires a good and admissible heuristic functions to reach the shortest-path (Madkour et al. 2017).

c. **RRT* Algorithm:** The RRT is a sampling-based algorithm that only finds feasible paths; it cannot be used for path planning optimization. RRT is a space filling tree that start from a randomly drawn samples and incrementally grows towards unknown areas (Bohács et al. 2016; Karaman and Frazzoli 2011). Karaman and Frazzoli (2011) proposed the RRT* and introduced path cost for optimizing motion planning by finding the least cost path.

d. **GA Search Algorithm:** In construction sites, the optimal path is not necessarily the shortest one. Beside other criteria such as safety and visibility, shortest path can be one of the search criteria. GA is a well-suited algorithm for such multi-criteria optimization problems. It is the most efficient optimization algorithm if numerous criteria are required. GA is a stochastic algorithm with probabilistic search rules that mimics genetics and the process of natural election by random yet directed search process to find the fittest (optimal or near optima) solution. It starts with a randomly generated population of candidate paths coded in binary strings and an objective function that evaluates their fitness as solutions based on a set of properties and variables. A string represents a path by the number of corresponding intermediate path nodes between the start and destination points. The objective function minimizes the distance by minimizing the number of path nodes. It also takes into account the constraints in which, for example, some nodes may have a large value proportional to the number of grid cells that lie on the undesirable, unsafe, or forbidden areas. Then, it applies reproduction operators (crossover and mutation) to generate new offspring solutions (Bohács et al. 2016).

2.5 Research on Workers' Safe Behavior on Site

In the field of construction management, many studies have been developed to improve safety including safety awareness (Saarela, Saari, and Aaltonen 1989), unsafe acts (Choudhry 2012; Duff et al. 1994), safety training (Hale 1984), and unsafe working conditions (Chi, Han, and Kim 2013; Haslam et al. 2003; Khosravi et al. 2014). Many studies have concluded that unsafe work practices of the workers and unsafe working conditions are a major cause of accidents and the resulting injuries, Figure 2.5 (Chi et al. 2013; Choudhry and Fang 2008; Haslam et al. 2003; Wu et al. 2015; Zhang and Fang 2013). Traditionally, safety is evaluated through the analysis of incident-related data such as the number of injuries, frequency and severity rates, and cost. This approach, however, have little predictive value as it only provides information about the rates of incidents and system failures without revealing the causes and their effects that would drive corrective actions and improvement measures (Carder and Ragan 2003; Cooper and Phillips 2004; Wu et al. 2015). Choudhry (2014) indicated that traditional safety performance evaluation approaches paid less attention to internal factors such as safety culture, safety attitude, safety behavior, and safety climate. Thus, behavior-based intervention approaches have been used and given increasing attention in both academia and practitioners (Fang, Wu, and Wu 2015).

(Responses from 2010 USW Health, Safety and Environment Conference Delegate Survey)

- Lack of or inadequate training
- Downsizing/understaffing
- Production pressures
- Increased work loads/intensification of work
- Discipline for Safety- blaming workers
- Equipment not properly maintained or repaired
- Job combinations
- Ergonomic hazards
- Heat
- Employer not addressing identified hazards

Figure 2.5. Health and Safety Concerns (Based on USW 2012)

Behavior-Based Safety (BBS) is a behavior-based intervention approach that draws great attention (Fang et al. 2015). It can be generally described as the process of determining and modifying unsafe behavior by providing methods and tools for workers to use to take control over their own safety performance (Scott Geller 2001; Zhang and Fang 2013). In construction, BBS is a top-down process where supervisors observe the behaviors of workers and provide guidance and/or implement positive or negative intervention. However, current BBS practices do not sufficiently consider management behavior, which may result in a superficial and nonpersistent impact of workers unsafe behavior. Considering management behavior can help in designing better BBS intervention approaches that can have a greater impact on worker safety behavior. Safety performance can be significantly improved if management is committed to apply effective safety behavior measures (Choudhry 2014). Management behavior is a major antecedent of worker safety behavior that is considered the root cause of occupational safety accidents and, therefore, it is increasingly gaining the academic attention (Fang et al. 2015). The complexity and variability of construction sites, misplacement of workforce and machinery, and the workforce high mobility on site make it difficult to implement safety management plans and greatly increase the uncertainty of the intervention outcomes (Ghasemi et al. 2018; Zhang and Fang 2013). Thus, computer modeling and simulation is a very useful approach in dealing with such problems.

Behaviors can be defined as actions or reaction in response to internal or external stimuli (Choudhry 2014). Acting safely may require sacrificing comfort and convenience. Safe behavior is a collective phenomenon that is attributed to management commitment to safety, team safety climate, and personal safety responsibility (Xu, Zou, and Luo 2018). Unsafe behavior is a decision made by the worker and could be triggered by several factors related to the worker himself, supervision and management, and unsafe conditions (Khosravi et al. 2014; Xu et al. 2018). The factors related to the workers include age, experience, attitude, motivation, intended acts, unintended acts, lack of training, getting the job done, and discipline for safety. Supervision and management factors include effective enforcement, supervision style, safety engagement, communication, competency, policy and plan, competing priorities, safety climate and culture, lack of availability of materials or equipment, and performance pressure. The unsafe conditions related factors include hazardous operation, construction stage, poor housekeeping, and equipment (Chi et al. 2013; Choudhry 2014; Choudhry and Fang 2008; Haslam et al. 2003; Khosravi et al. 2014).

In order to have an unsafe behavior there has to be a hazard or an unsafe condition, Figure 2.6. Such unsafe conditions include crushing, noise, vibration, chemical, gases, dust, mists, fumes, lifting, fire, slips, trips, fall, electrical, and heat. The most likely behavior to happen is the favorable, under greater pressure, and/or the easier behavior. Typical worker behavior to such conditions is to duck, dodge hazard, avoid hazard spots, or leave hazard location. Consequently, the other type of behavior is to keep working and not paying much attention to the hazardous situation (non-avoiding or aggressive behavior). Therefore, these two types of behaviors are the important ones to be considered in this study. Often, workers cannot identify unsafe conditions and, therefore, it is the responsibility of the management to identify and correct unsafe conditions in advance. BBS analysis (Figure 2.7) start by identifying the hazard through data analysis, worker observations, interviews, surveys and questionnaires, government regulations, and inspections. Then, evaluating the situation through risk analysis and prioritize hazards. After that, controlling the hazard through elimination/substitution, engineering controls, warning, training and procedures, and personal protective equipment. (USW 2010; Xu et al. 2018).

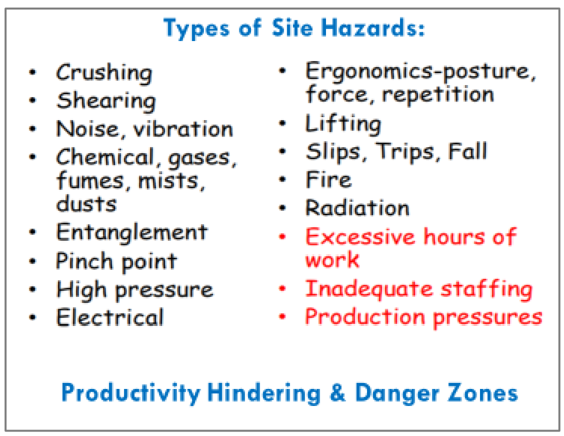


Figure 2.6. Types of Hazards on Construction Sites (Based on USW 2010)

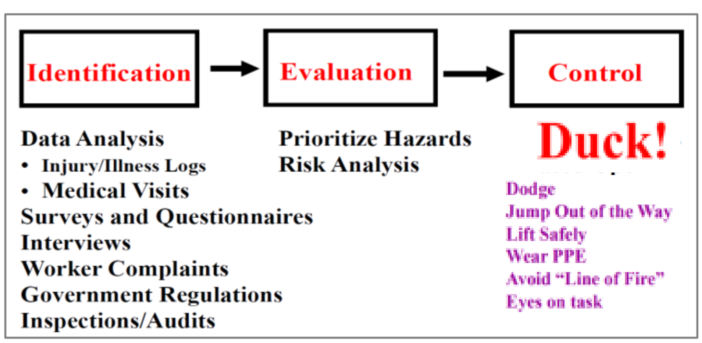


Figure 2.7. Behavior Based Safety: Modeling vs. Worker Behavior viewpoints (USW 2012)

2.6 Conclusion

This chapter presented a review of relevant literature and the research developments in current site layout planning models and methodologies, along with their characteristics and limitations. As noted in the literature, construction site layout planning is a complex problem involving a large number of interrelated variables and factors that interact with each other in a temporal-spatial manner. Most of the reported research efforts have addressed this problem from a macro perspective and did not look at the detailed interactions between the workers and the site. As such, a micro-level analysis is needed to provide a better understanding of site layout needs.

Chapter 3

Agent-based Simulation Framework for Site Layout Optimization

3.1 Introduction

This chapter provides an overview of the proposed ABMS framework for site layout planning that integrates agent-based simulation with a GA optimization procedure to maximize productivity and safety, as well as minimize accident/injury potential during construction. It discusses the site layout quantification parameters and presents the development of the ABMS simulation model with details about its main components. A hypothetical case study example is then presented to demonstrate agents' behaviors and their self-determined paths around obstacles. It also illustrates how the ABMS model provides a more realistic approach to simulating and representing construction processes, accordingly producing accurate assessment of site productivity and safety.

3.2 Proposed Framework for Agent-based Site Layout Optimization

The proposed framework consists of two main components, as shown in Figure 3.1: ABMS Model (discussed in next section); and GA Optimization Model (discussed in chapter 5).

The proposed ABMS model was developed to simulate real site conditions including site characteristics and workers' behaviors, and simulate actual construction operations within the site. It captures the interactions between workers and objects on-site, and thus can produce more realistic assessment of productivity and accident/injury potential as a result of crowded locations and obstacles. Once the ABMS model is developed and verified (as discussed in next section), the optimization algorithm (chapter 5) becomes necessary to try thousands of combinations of site characteristics and possible locations of site facilities until an optimum site layout with maximum productivity and minimum accident potential is determined.

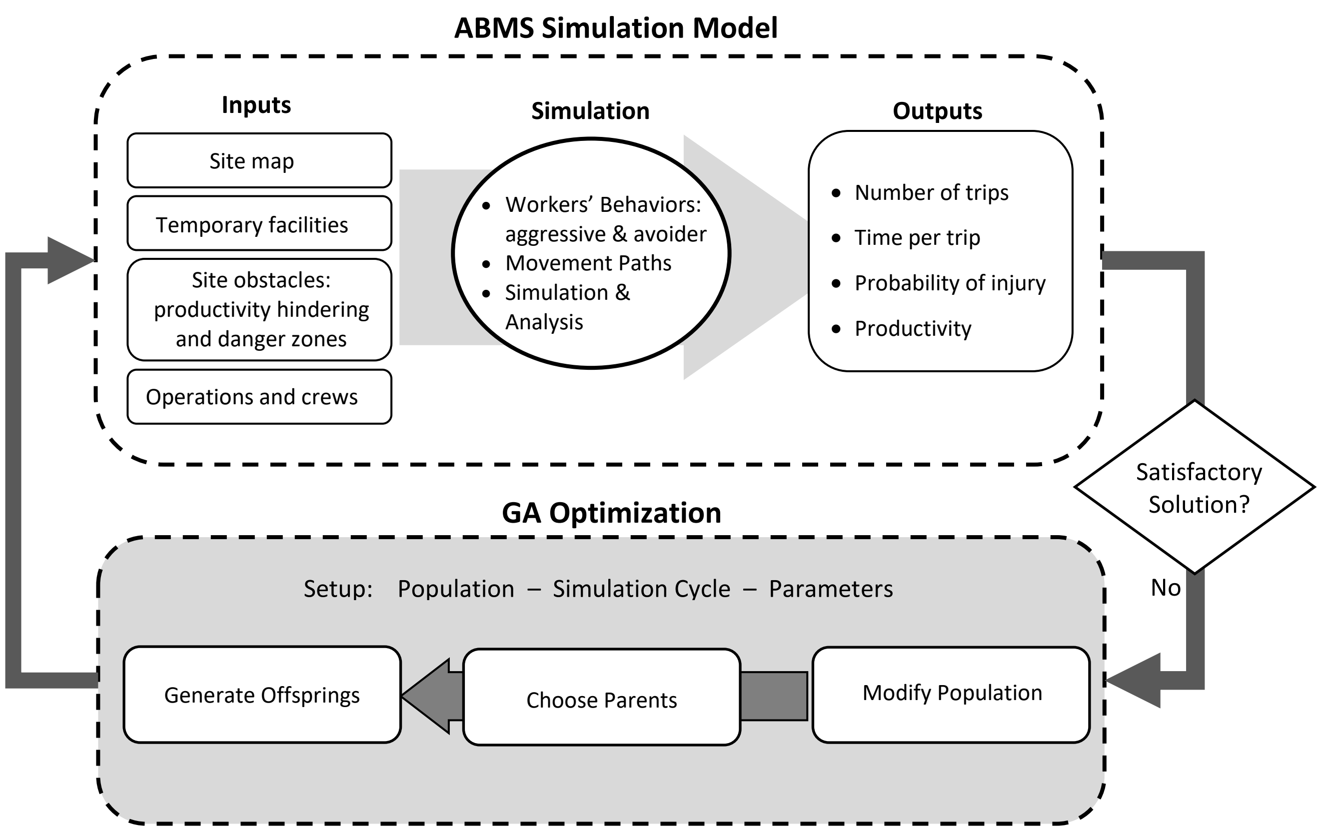


Figure 3.1. ABMS Optimization Framework for Site-Layout Planning

To achieve its decision-support goal, the framework has been designed with:

- Simple user interface to facilitate a high level of interaction with the user;
- Powerful analysis of work flow and object interactions, considering possible conflicts and collisions;
- Visualization tool for construction operations; and
- Sensitivity analysis and multiple what-if scenarios.

3.3 Agent-Based Simulation Model

As shown in Figure 3.1, the ABMS model incorporates three subcomponents: inputs; simulation; and outputs. The details of these subcomponents are as follows:

3.3.1 Model Inputs

The developed ABMS simulation model enables the creation of a detailed visual model of the construction site and specifying four types of construction-related information; site map, temporary and fixed facilities, site obstacles, and operations and crews, as follows:

(a) Site map (Figure 3.2): The model accepts site maps with any shape and size and simulates any number and type of crews with any number of workers. The site map can be Imported as a color-coded image file that defines the site geometry (locations, sizes, and shapes), along with the roads, entrances, and the construction area.

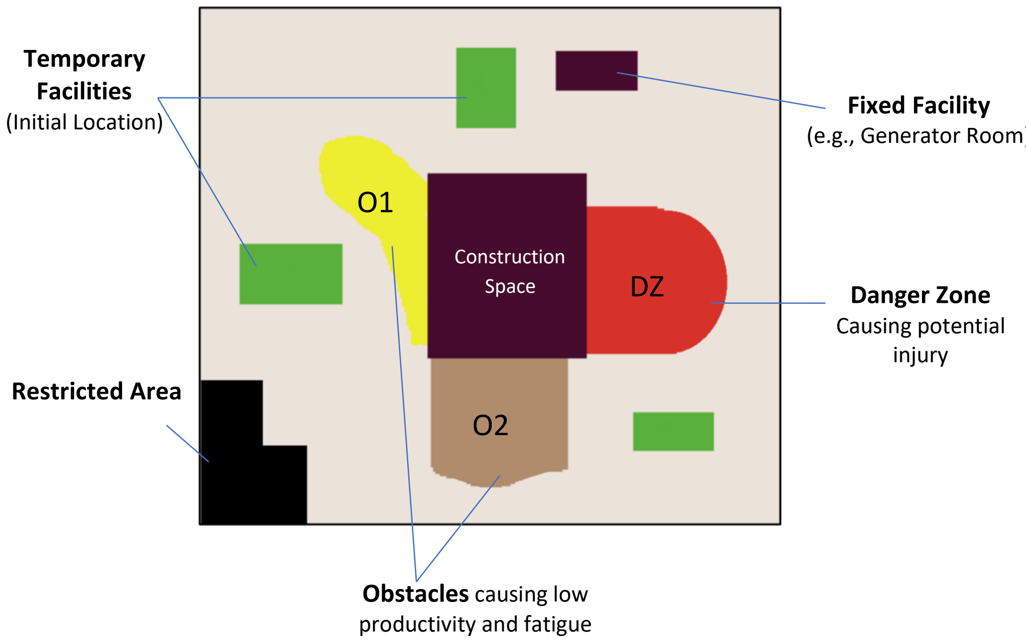


Figure 3.2. Sample Site Map with Facilities and Obstacles

(b) Fixed and Temporary Facilities: Facilities are defined on the site map (e.g., Figure 3.2) with their size and location. While fixed facilities are the permanent facilities that require certain fixed locations such as existing buildings, trees, fire hydrants, roads, or the restricted area and the construction space in Figure 3.2, etc. Temporary facilities, on the other hand, are the facilities required to support the construction operations such as storage yards, batch plant, fabrication shops, site offices, equipment locations, etc. The simulation model accepts facilities' IDs; coordinates (locations); and dimensions. This information can be imported directly from a file. Later as discussed in Chapter 5, the locations of temporary facilities are considered as variables to be optimally determined by the optimization procedure so that safety and productivity as highest;

(c) Site Obstacles: The model accepts the locations and dimensions of various site obstacles (as shown in Figure 3.2). These obstacles can be color-coded and read automatically from the site map file. The obstacles affect worker's behaviors in one (or more) of three effects, as follows:

- ***Effect (O1)*****:** This obstacle slows down the workers (e.g., crowded area), which leads to working less efficiently;
- ***Effect (O2)*****:** This obstacle causes workers' exhaustion and fatigue (e.g., dusty, and noisy areas), which makes the worker lose energy and stop working earlier (gets tired); and
- ***Danger zone (DZ)*****:** Exposure to this obstacle causes a worker to be eliminated according to a *predefined* probability of injury which is entered by the user.

Any obstacle can also combine any of the above three effects. For example, an obstacle can slowdown the workers' movement, cause exhaustion, and is also a danger zone. An obstacle thus can allow workers to move on it with a specific moving speed (slower than regular walking speed). For practicality also, different crews can have different sensitivity to different types of obstacles.

(d) Operations and Crews: The activities' and workers' information include the number of workers in a group (e.g., bricklayers), their source facility, their destination facility, and the time required to perform the work, as a normal distribution with mean and standard deviation. Each group of workers can be assigned to be sensitive to specific types of obstacles, as an ON/OFF.

3.3.2 ABMS Simulation Model

Once all site information have been specified, the first step before carrying out simulation analysis is to configure the agents' behaviors and let each agent type decide the possible movement paths around the facilities and obstacles on site.

a. Agents' Behaviors

As discussed in the literature, several studies addressed path planning on construction sites with the objective of finding the safest and/or shortest path for workers and equipment while moving between work locations (e.g., Bohács et al. 2016; Cheng and Mantripragada 2012; Rahman et al. 2016; Soltani and Fernando 2004; Zhang and Hammad 2012). In the present research, agents that are faced with an obstacle behave in one of two common ways, as follows:

Avoider Behavior: This applies to workers who are cautionary and do not take chances by moving within obstacle zones and avoids them all together; or

Aggressive Behavior: Applies to the workers who are less cautionary and take chances by moving into obstacle zones to save time or to avoid the congestion of regular routes.

Because agents can be positioned in different locations within a facility, they have multiple directions to start from. To establish agent behavioral rules that reflect workers' attitudes, this research introduces two methods (forward-backward and shortest path) to determine agents' movement paths between work locations. The two methods are designed to mimic the workers' behavior in selecting the path between each two work facilities and locations, which are variation of the visibility graph approach presented in Chapter 2. The basic assumption in path planning is that agents have full knowledge about the planned route and other agents. Avoider agents always try to avoid congestion and obstacle areas; while aggressive agents use their judgment to use the shorter riskier path to reach quickly to destination. The two autonomous path determination methods are discussed in the next two subsections.

b. Agents' Behaviors: Forward-Backward Path

This method involves forward and backward trips by test agents from source to destination facilities, where the backward trips are used to refine the paths of the forward trips. The method starts by sending ten test agents of each type, five maneuvering right around obstacles and five maneuvering left. Once a test agent reads its random location within a source facility, it moves step-by-step towards the destination, considering its behavior type (avoider versus aggressive), and records its path. Among all the possible paths produced by the test agents, the shortest two paths between two facilities are selected; one for the avoider and the other for the aggressive agents. Test agents perform their stepwise movements according to a maneuvering rule that limits their directional deviation to 3 to 5 degrees, according to the following rules (Figure 3.3 and Figure 3.4):

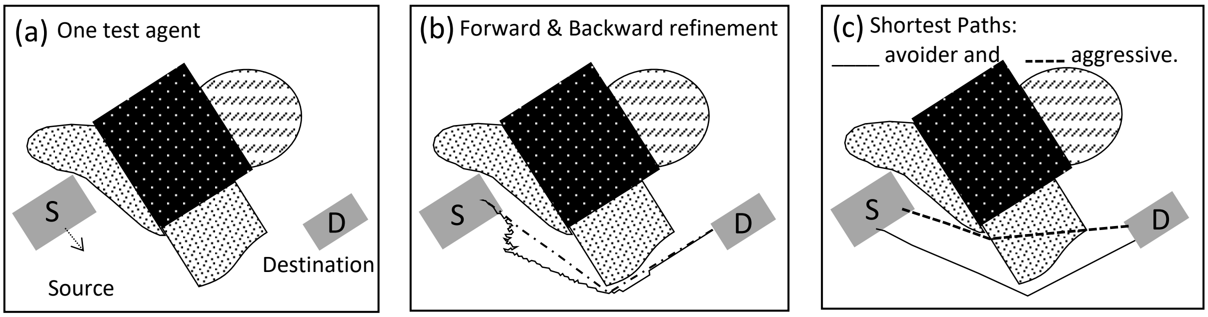


Figure 3.3. Steps in Forward-Backward Path from a Source to a Destination

1. Select a random test agent (avoider or aggressive), with a random right or left direction (Figure 3.3 (a));
2. The test agent orients itself to face the destination location;
3. Check for a clear path (straight path without obstacles) to the destination from current location;
4. If there is a clear path to the destination, move towards it and skip to step 8;
5. Alter own direction between 3 and 5 degrees, towards the destination;
6. Check for a clear path at a predetermined distance ahead. If there is no clear path, go back to step 5;
7. Move one step forward, add this point as a mark in this path, and repeat the process from step 3;
8. If the destination is reached, travel back to the start point by following the farthest mark that can be reached in a straight line;

9. Record the backward path and use it as a refined path for forward movement (Figure 3.3 (b));
10. Repeat the previous steps for all test agents; and
11. Select the shortest path of all test agents (Figure 3.3 (c)) between each two facilities and later use it in the simulation.

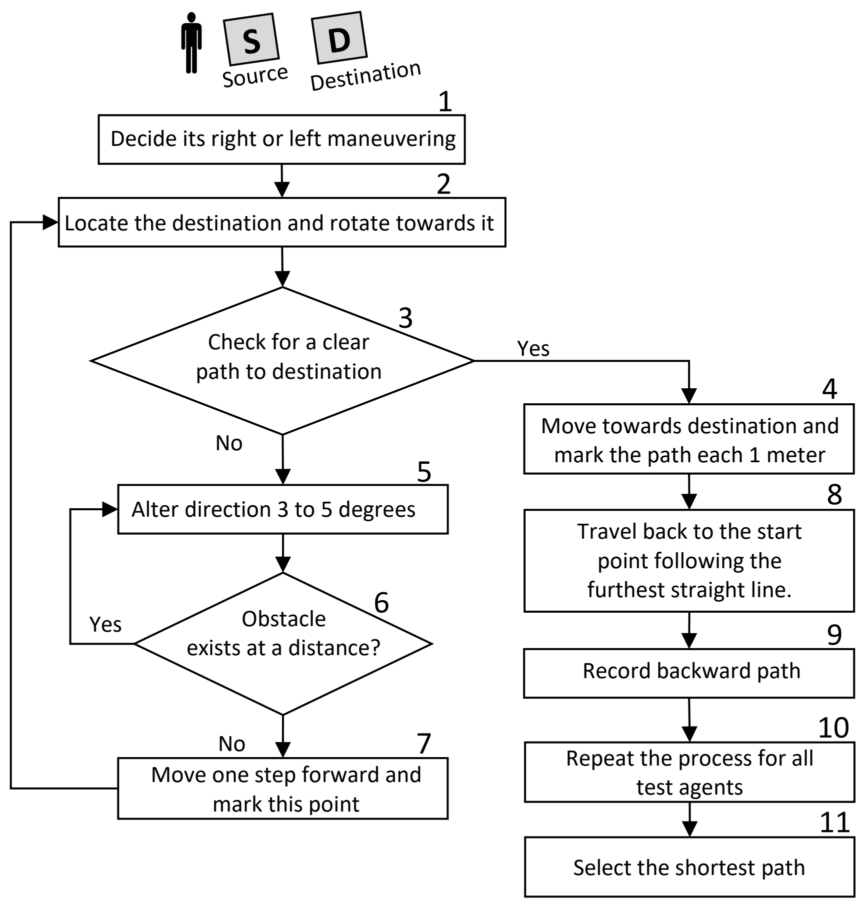


Figure 3.4. Procedure for Forward-Backward Path Determination

c. Agents' Behavior: Shortest Path

In this method, the agent searches for the shortest path by repeatedly searching for the closest edge of the obstacle or facility located in its path and use it as a temporary destination point in order to get to the destination location. The agent first reads its random location within a source facility and checks for facilities or both facilities and obstacles, considering its behavior type (avoider versus aggressive), in its path to the destination. To move around them, the agent searches for the closest edge and assign it as a temporary destination point. Then, the agent moves towards that point and repeats the process until it reaches the destination. The difference between the aggressive and avoider types of behaviors is that avoiders avoid walking through facilities, restricted areas, and obstacles; while aggressive agents avoid facilities and restricted areas but walk through obstacles. The detailed step by step description of the process for both types is as follows, Figure 3.5 and Figure 3.6:

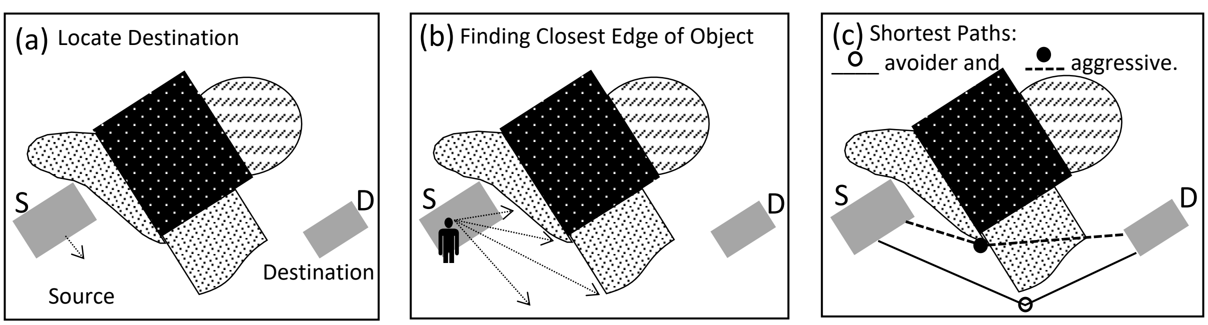


Figure 3.5. Steps in Shortest Path Finding Method from A Source to A Destination

1. The agent orients itself to face the destination location;

2. Check for a clear path (straight path without avoided objects) to the destination from current location;
3. If there is a clear path to the destination, move towards it;
4. Search for the closest edge of the avoided object(s) and assign it as a temporary destination point;
5. Move towards the assigned temporary destination point;
6. If the temporary destination point is reached, go back to step 2.

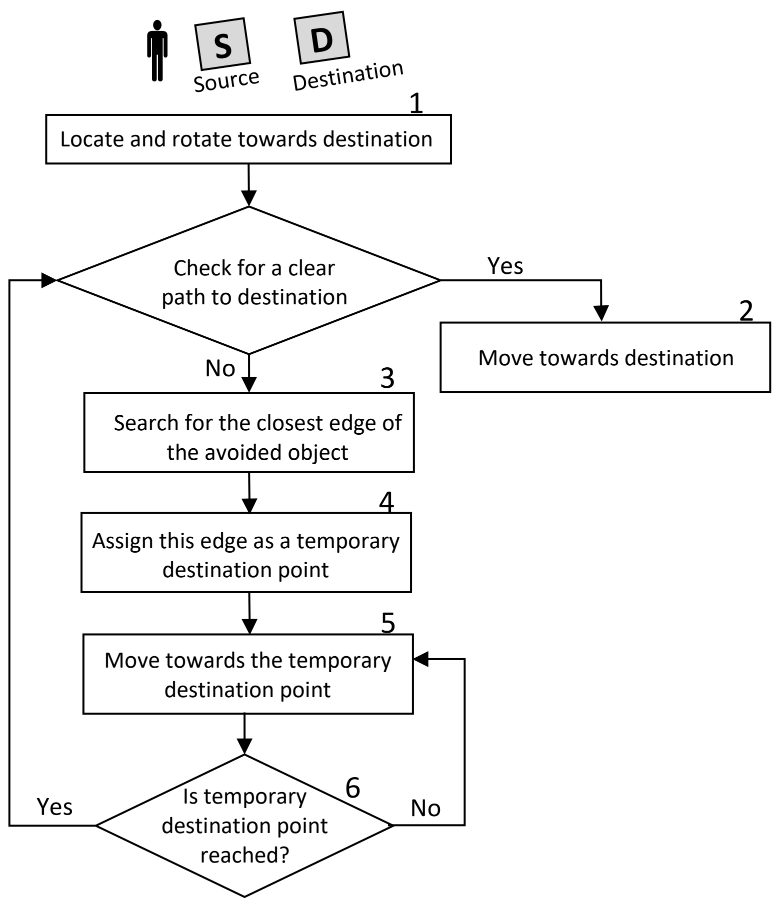


Figure 3.6. Procedure for Shortest Path Determination

d. Simulation Process

After setting up the construction site and determining the movement paths, full simulation of the work operation on site can be carried out for a whole workday. The result of the simulation run enables the analysis of the impact of site characteristics on productivity and safety by tracking the agents' on-site movements and recording statistics about work progress and safety issues. The considered interactions of agents with each other and with the environment are the ones related to their movement around the site. For example, to simulate crowdedness and its effect on movement, agents cannot step over each other and each spot occupies one agent at a time. To avoid agent collision, a buffer zone is created around facilities, obstacles, and agents. In addition, a separation distance is introduced between the opposite directions on each path. In the current stage of model development, interactions that are related to performing the tasks such as information exchange are not considered. The simulation starts by generating the number of agents (workers) required at each site facility. At the start of a workday, each agent performs its construction operation according to the following process (Figure 3.7):

1. If work is required at current location, perform task according to its duration;
2. According to the agent type (avoider or aggressive), retrieve the path to the destination;
3. If there is an obstacle on the next step of movement, then identify its type and apply its effect (O1 move slowly, O2 lose energy, and DZ apply injury probability);
4. If no obstacle in step 3, apply normal movement;
5. Move one step forward on the path;

6. If destination is reached, go to step 7, otherwise, move back to step 3;
7. If destination is reached and a construction task is required, perform the task; and
8. Once work is complete, proceed to next location, repeat from step 2.

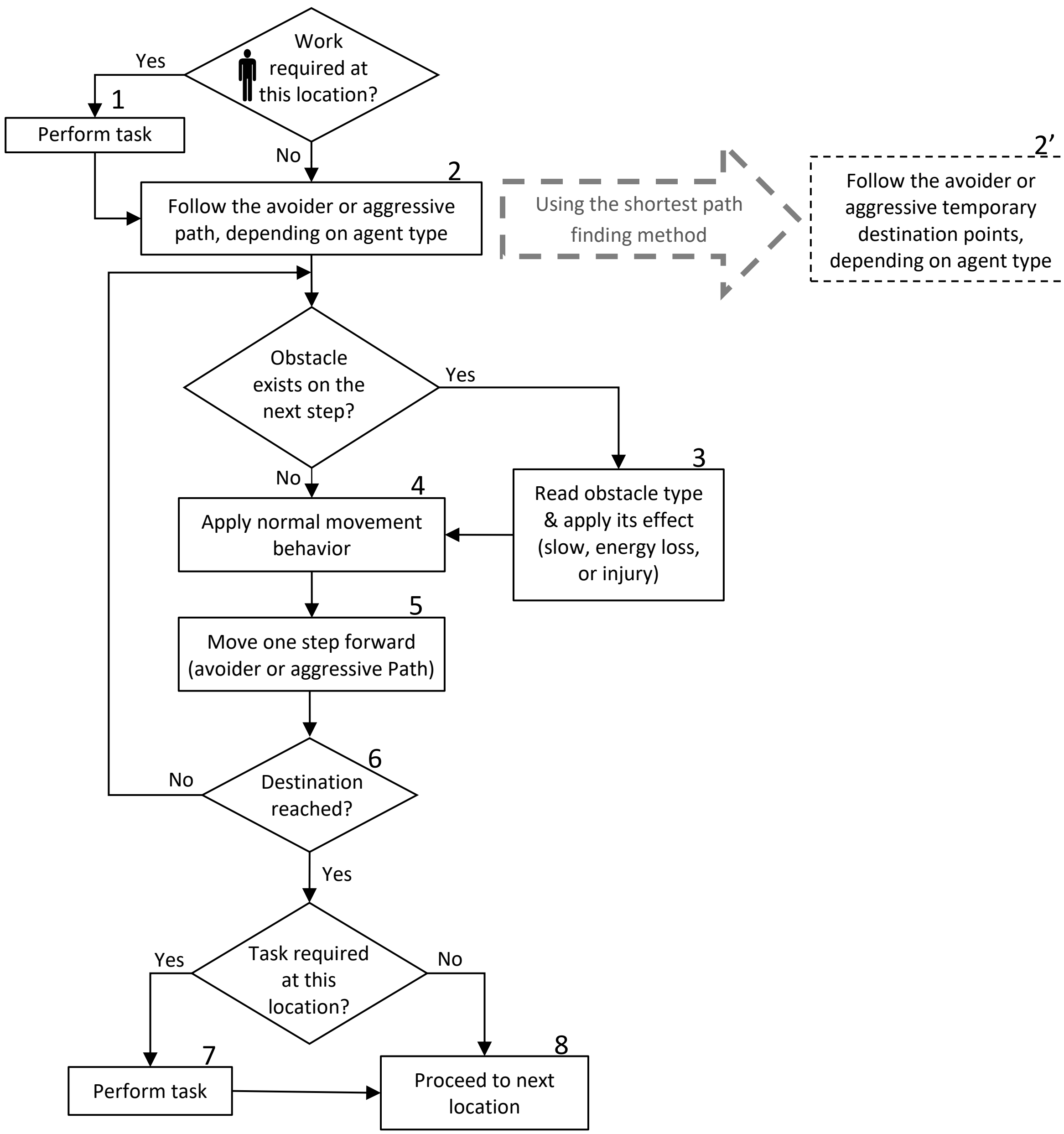


Figure 3.7. Simulation workflow

3.3.3 Model Outputs

Productivity evaluation is performed by assessing the simulation result with respect to the quantity of work performed in a certain period of time. The model tracks and records the number and time of each trip between every two work locations for all types of agents (workers and equipment). It also tracks and records the performance data for agents’ tours (moving between multiple locations). A trip starts when an agent reaches (or starts in) a work location, performs the required task, travels to the next work destination, and the trip finishes when the agent reaches the next destination. A tour, on the other hand, includes performing tasks and traveling between multiple locations. For example, if an agent is assigned to work in locations 1, 2, and 3, respectively. One trip includes performing the task in location 1 and traveling to location 2. While one tour includes performing the task in location 1, traveling to location 2, performing the task in location 2, traveling to location 3, performing the task in location 3, and traveling back to location 1. Figure 3.8 shows a description of the model’s tracking procedure of site productivity.

At the end of the simulation, different types of outputs are generated to reflect the effect of the site organization and the locations of obstacles on tasks’ durations. First, the model calculates the number of workers in each location and path and the average number of trips for each group of workers between work locations. It calculates the average time and number of complete round trips for the workers with multiple destinations. It also calculates the average trip time for all paths on-site and the number of workers injured in danger zones. Since workers passing certain obstacles get tired fast, the average time for such workers is calculated as well. Equipment crews' productivity performance evaluation is calculated in the same manner and shown separately in the output CSV files. Based on these calculations, site productivity and safety are then assessed.

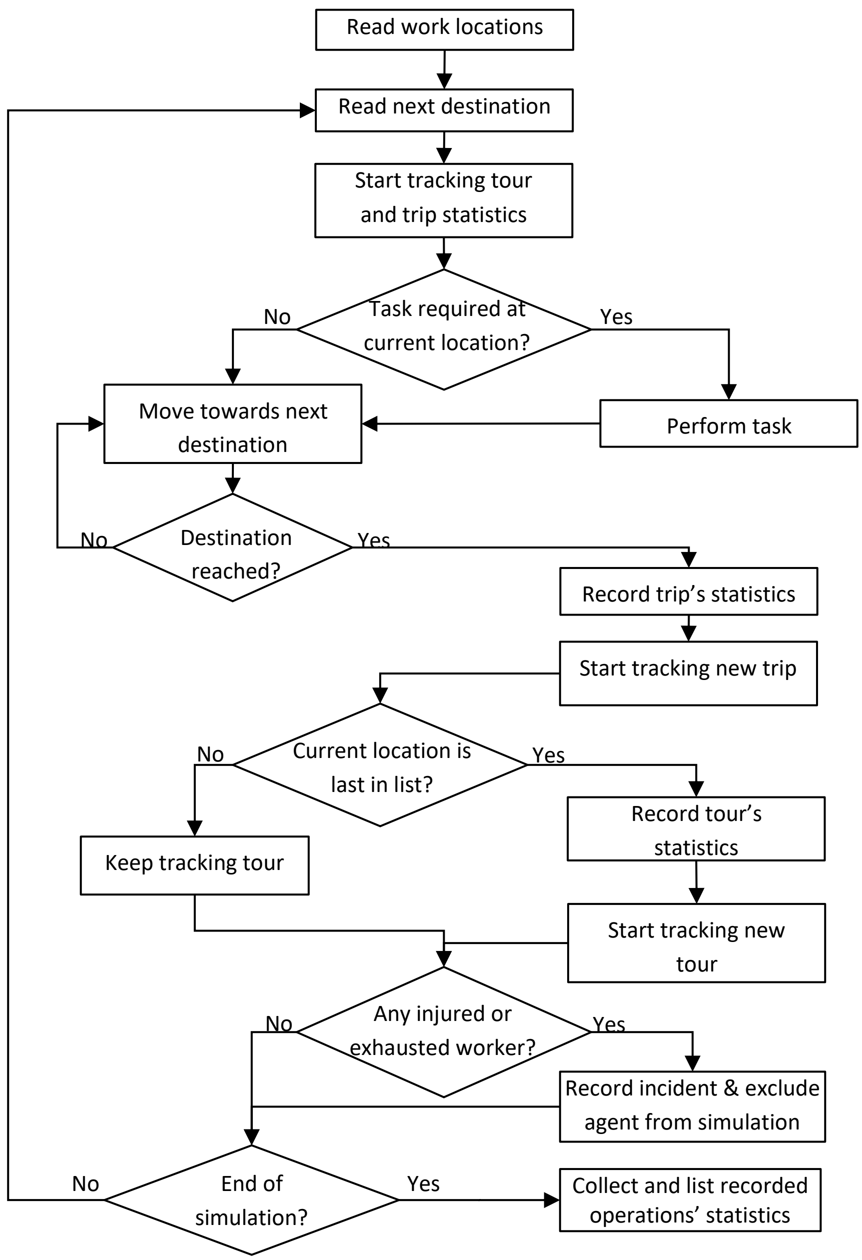


Figure 3.8. Model's tracking of Site Productivity

Based on the simulation results, the quality of a site layout can be quantified according to several parameters. The most important parameters are access, distance, safety, and work environment (Figure 3.9). The proposed simulation model considers these parameters for the evaluation of site layout plans:

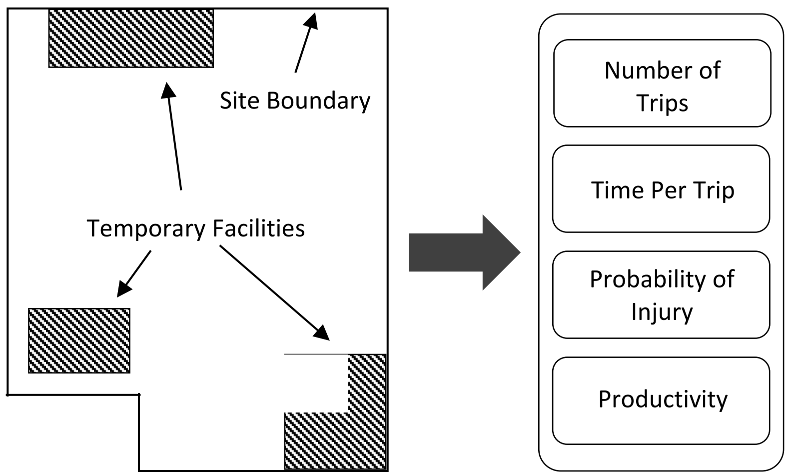


Figure 3.9: Parameters for Evaluating a Site Layout

- **Access:** In the model, site access locations are not considered available spaces for placing temporary facilities. The importance of this consideration is that access insures the flow of equipment, materials, and workers to and from the construction site, and accordingly ensures work progress. Moreover, access should be available at all times for emergency vehicles when needed.
- **Distance:** In the case of heavy traffic of material, equipment, or workers between two facilities, distances between facilities should be as short as possible. The simulation model evaluates the effect of distance between facilities by measuring the total trips achieved. Intersections between workers' paths also affect the number of trips (productivity). Accordingly, this factor is

also accommodated in the evaluation of a certain site layout and affects its score (Total number of trips).

- **Safety:** This factor is highly influential in designing site layout plans. In construction, many situations related to safety affect site layout planning and facilities allocation. For example, falling objects from cranes is a known safety issue that force workers to move around cranes movement area. In the simulation model, two worker groups with different behavior types, avoiders and aggressive, are simulated. The avoiders group move around the danger area. On the other hand, the aggressive group move through the danger area. Accordingly, the two behaviors can be assessed and compared.
- **Work environment:** Good working environments can greatly affect progress and workers' productivity. Construction operations involve several sources of discomfort such as noisy machinery, dusty areas, and muddy surfaces. The simulation model evaluates the effect of such sources on productivity and work flow for the purpose of minimizing their negative effects and optimizing site layout plans.

3.4 Implementation and Comparison of Workers' Paths

The proposed ABMS simulation model was implemented on the multi-agent programming language and modeling environment NetLogo (Tisue and Wilensky 2004), which is one of the powerful web-based tools on the market.). NetLogo was selected because it has: (1) a visual interface that reads the work environment (construction site) easily from a color-coded image file; (2) an easy-to-use programming language; (3) strong input/output capabilities to Excel and other programs; (4) a wide range of additional modeling features such as system dynamics and optimization features; and (5) free access to the software on the web. To develop the proposed model, NetLogo was used to incorporate:

- A simple user interface with all parameters being clear to the user;
- Visualization of construction operations on site; and
- Sensitivity analysis and multiple what-if scenarios.

The model took some effort to learn the programming language and to master the development tool. The model includes an extensive code (Partly shown in Appendix A). Figure 3.10 shows the developed interface that facilitate data input.

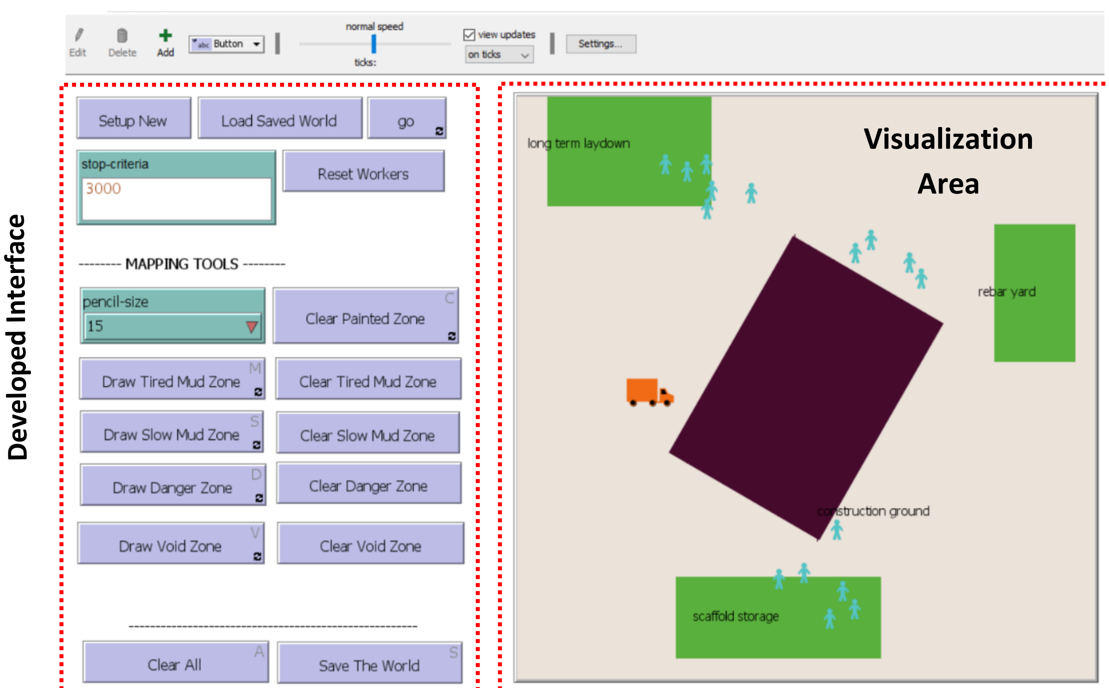


Figure 3.10. Developed Model Interface

3.4.1 Hypothetical Case Study

To verify the model development and test its work, a site map was created by reading input files with the site plan (Figure 3.11). In this case study, the site grid size (patch) is 1m x 1m and the average worker speed on site is 1.7 km/h.

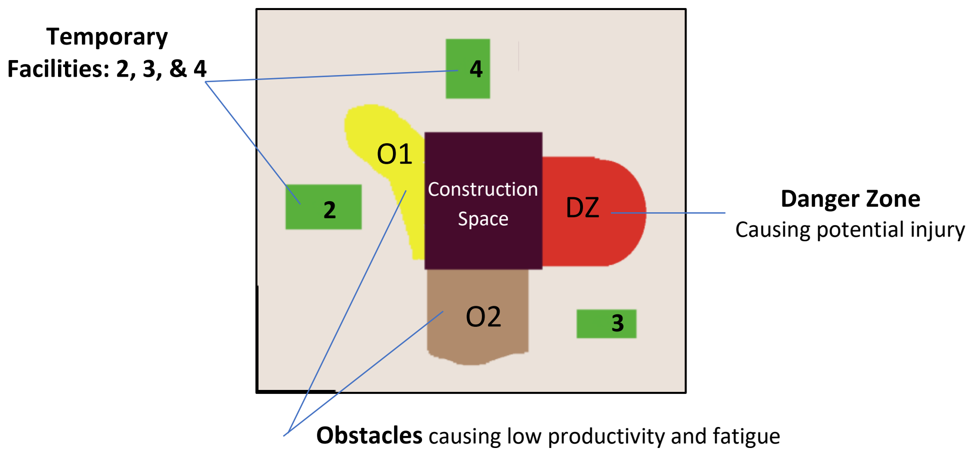


Figure 3.11. Site Map of the case study with Facilities and Obstacles

The model simulates a worker's crossing 1 patch in each time unit (tick). Accordingly, 1 tick in the model equals to 2.12 sec in real time. The case study site is 8,250 m2 (110m x 75m) with the construction space being 1,000 m2 (35 m x 30 m). It involves types O1 and O2 obstacles, a danger zone (DZ), in addition to three temporary facilities (numbered 2, 3, and 4) with 10, 13, and 8 workers, respectively (Table 3.1). The effect of Obstacle 1 is set to reduce the workers' movement speed to 0.5 the normal speed (0.5 patch/tick). Workers in the model start with a balance of energy points that allow them to work to the end of the day. Accordingly, the effect of Obstacle 2 is set to cause the workers passing through it to lose double the normal energy loss, where the normal energy loss is 1 energy point per 1 movement step, which equals to 1 unit of time (tick). On the other hand, the probability of injury at the danger zone is set to 2%, which is low and may not result in an injury every simulation run (day). At the start of the simulation, the workers in each location are split into Avoider and Aggressive groups. The destination of the workers in each facility is shown in Table 3.1.

Table 3.1. Workers and Facility Information

Facility	Number of Workers	Destination	Task Duration (min.)		Dimensions (m)	
			At Source	At Destination	Width	Length
2	10	Facility 4	25	5	25	15
3	13	Facility 2 and Facility 4	40	10	20	10
4	8	Main Building 1	40	10	15	20

In addition to the site plan, inputs to the developed model are read from Excel data files related to three types of inputs (as discussed earlier in section 3.3.1): facility data (Figure 3.12); color-coded areas on the site map (Figure 3.13); and the crews and work operations (Figure 3.14). Figure 3.12 shows Data input of the coordinates, dimensions, and rotation angle of the facilities on site. The coordinate system used considers the middle point of the visualization area (Figure 3.11) as the site origin.

				Facility Coordinates		Facility Dimensions		Facility Rotation
	A	B	C	D	E	F	G	H
1	facility	type	name	x	y	width	height	angle
2	1	fixed	construction ground	0	0	180	0	300
3	2	moveable	long term laydown	-128	175	120	90	0
4	3	moveable	rebar yard	166	68	60	100	0
5	4	moveable	scaffold storage	-20	-165	150	60	0

Figure 3.12. Facilities Input Sheet

Figure 3.13 shows Color-coded data for all the spaces on site with the relative workers speed on each color, permissible and restricted areas, etc. For example, the site in Figure 3.11 has the color beige as the permissible area for workers to move within. For each color, the movement speed factor (multiplier), relative energy consumption, and injury potential is defined. This enable full flexibility in defining which color represents which type of obstacle.

		Speed Factor	Energy Consumption	Probability of Injury
		D	E	F	G

		D	E	F	G
	1	colour name	speed	energy	injury
Accessible Area	2	beige	1	1	0
Obstacles	3	light brown	0.5	1	0
	4	orange	1	1	2
	5	light yellow	1	2	0
Temporary and Fixed Facilities	6	green	1	1	0
	7	dark purple	1	1	0
Restricted Area	8	black	1	1	0

Figure 3.13. Color-Coded Objects on the Site Map & their Characteristics

The last table of input data (Figure 3.14) relates to the crews and work operations that is expected to happen on site. Sample Input Data for an aggressive crew is shown in Figure 3.14 with the work Sequence, typical moving speed (1 means normal speed), and the workers' sensitivity to various types of obstacles (all turned ON in Figure 3.14). Because the model is flexible to accept data either from the interface or by importing files, Table 3.2 summarizes the data entry methods possible.

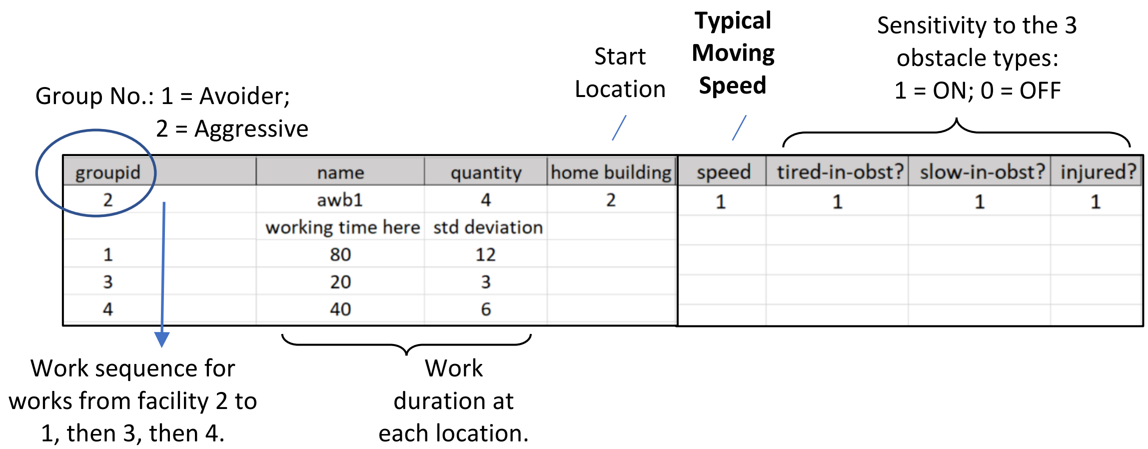


Figure 3.14. Sample Input Data for Crews and work sequence on site

Table 3.2. Layout Information and Input Methods

Data	Input Method		
	Bitmap File	Excel File	Model Interface
Site Boundaries	✓	✓	-
Main Buildings	✓	✓	-
Roads	✓	✓	✓
Obstacles	✓	✓	✓
Number of Temporary Facilities	-	✓	-
Location of Temporary Facilities	-	✓	-
Shape and Size of Temporary Facilities	-	✓	-
Number of Workers	-	✓	-
Destination	-	✓	-
Time to Perform Work	-	✓	-
Location of Obstacles	✓	-	✓
Shape and Size of Obstacles	✓	-	✓
Probability of Injury in Danger Zone	-	✓	-

As shown in Figure 3.14, the typical worker movement speed in normal conditions, no obstacles in the path, is considered as 1.7 Km/h (1 is normal speed, 2 is double the normal speed). However, each crew can have different movement speed (e.g., equipment vs worker, loaded vs not loaded). Agents (workers and equipment) movement speeds within any obstacle is calculated by multiplying the typical speed in Figure 3.14, by the speed factor in Figure 3.13. Workers and equipment, in reality, do not move with constant speed. Therefore, the movement speed is modeled as normal distribution with a mean equal to the specified speed in the input files and a standard deviation of 10% of the mean.

3.4.2 Implementation of Forward-Backward Path

In this method, the movement paths are determined prior to the simulation, at the setup stage, for the workers to follow during the simulation. The model first reads the list of source and destination work locations for all types of agents (avoider vs aggressive, worker vs equipment). Accordingly, test agents are sent to determine the movement paths between work locations, as shown in Figure 3.15. During the simulation, agents perform construction operations by following these paths. Using this method, the model required 21 seconds to set up the site and determine movement paths; and another 50 seconds to simulate one day of construction operation. Table 3.3 summarizes the results of the simulation experiments. Due to the absence of obstacles between facility 4 and the main building (1), both the avoider and aggressive agents produced identical production (row 4 in the table). The first row in the table shows the case of aggressive agents taking slightly less time per trip and thus making slightly more trips. The second and third rows, on the other hand, show the aggressive agents taking noticeably more time per trip and thus making less number of trips. Overall, also, the potential for injury/accident of this site configuration is evaluated as 1 in 19 days (average in five runs), which is high. This is determined by applying the optimization with the simulation covering a long range of days, and recording when an accident occurs. Overall, this exercise verified the accuracy of the model, its sensitivity to the location of temporary facilities and characteristics of obstacles, sensitivity to worker's behavior, and its suitability for production estimation and enhancing the site layout. In the following chapters, a realistic building construction project will be simulated. The simulation model will be integrated with a GA optimization procedure that searches for the optimal locations of the facilities so that to either maximize the number of trips, minimize accident potential, or both. Moreover, finding the optimal site plan will involve finding the optimal behavior and movement oaths on-site.

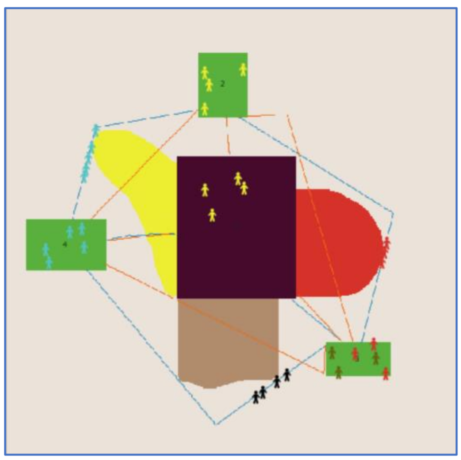


Figure 3.15. Forward-Backward Self-Determined Movement Paths

Table 3.3. Simulation Results with Forward-Backward Self-Determined Paths

Source and Destination	Avoider		Aggressive	
	No. of Trips	Min. / Trip	No. of Trips	Min. / Trip
2 to 4	15.3	31.5	15.4	31.1
3 to 2	9.4	50.9	9.0	53.3
3 to 4	8.9	54.0	8.7	54.9
4 to 1	10	48.0	10	48.0
Potential injury	-----		1 in 19 days	

3.4.3 Implementation of Self-Determined Shortest Path

Unlike the previous method, the movement paths in this method are determined during the simulation. While moving between work locations, each agent individually reads its surroundings searching for its own shortest path to its next destination. This is done by searching for the closest edge of the obstacle or facility ahead, depending on the type of agent. This process is repeated until the agent reaches the destination. Using this method, the model required 33 seconds to simulate one day of construction operations. Table 3.4 summarizes the results of the simulation experiments. Due to the absence of obstacles between facility 4 and the main building (1), both the avoider and aggressive agents produced identical production (row 4 in the table). The first row in the table shows the case of aggressive agents taking slightly more time per trip and thus making slightly less trips. The second and third rows, on the other hand, show the aggressive agents taking noticeably more time per trip and thus making less number of trips. Overall, also, the potential for injury/accident of this site configuration is evaluated as 1 in 13 days (average in five runs), which is high. This is determined by applying the optimization with the simulation covering a long range of days, and recording when an accident occurs.

Table 3.4. Simulation Results of Self-Determined Shortest Paths

Source and Destination	Avoider		Aggressive	
	No. of Trips	Min. / Trip	No. of Trips	Min. / Trip
2 to 4	13.8	34.5	13.4	35.2
3 to 2	9.4	50.5	8.8	54
3 to 4	8.7	55.1	9	53
4 to 1	9	52.8	9	52.8
Potential injury	-----		1 in 12 days	

As a general comment, while the methods use different behavioral rules for agents' on-site movement that may affect site productivity and simulation running time. In this comparison, a hypothetical case study relates to a construction site with different types of site obstacles was used (Figure 3.15). It was used to examine the self-determined path methods' performance and ability to mimic the actual site objects' movement behavior. It was also used to show the model's ability to capture and analyze work productivity in the presence of obstacles.

Overall, this exercise verified the accuracy of the model, its sensitivity to the location of temporary facilities and characteristics of obstacles, sensitivity to worker's behavior, and its suitability for production estimation and enhancing the site layout. Experimenting with two self-determined path methods verified the accuracy of both methods in modeling workers' movement and behavior within the construction site and around site facilities and obstacles. As the results show, both self-determined path methods produced very close productivity estimates. Considering that both methods are developed and built to achieve the same movement behavior and goal, it expected to have such outputs. However, the forward-backward method required a total simulation running time of about 70 seconds; while the shortest path method took 30 seconds. This difference in speed is expected in small size cases, however, it is expected that in large case studies, determining the paths at the beginning can save simulation time. The importance of simulation time is that in the following chapters, a realistic building construction project will be simulated. The simulation model will be integrated with a GA optimization procedure that searches for the optimal locations of the facilities so that to either maximize the number of trips, minimize accident potential, or both. Moreover, finding the optimal site plan will involve finding the optimal behavior to encourage (avoider vs aggressive). As such, further simulation for larger sites will utilize the method that will take less simulation time.

3.5 Conclusions

This chapter introduced the proposed site layout planning ABMS framework. It presented the details of developing and applying the ABMS simulation model for simulating construction operations involving different human behaviors and self-determined path methods for analyzing and assessing productivity and safety of construction site layouts. The ABMS model simulates avoider and aggressive workers' behaviors around variety of site obstacles, and accordingly assess site productivity and safety. Two self-determined path methods are compared and verified using an example case study. The model is capable of handling different conditions, site shapes, numbers of facilities, facility sizes, obstacle types, obstacle locations and sizes, and number of workers. The model assesses productivity and safety in construction operations at the micro level, by modeling the workers individually and assessing the effect of their behaviors, which is expected to be an important step towards site layout optimization. This model can help project managers find the causes and circumstances of productivity loss and suggest realistic improvement solutions. The ABMS model was demonstrated on a hypothetical case study to verify its effectiveness and the ability of agents to autonomously determine their preferred paths around obstacles. The experiment results show that the model is a valuable tool for analyzing and assessing the effect of workers' behaviors on productivity and safety, in the presence of obstacles.

Chapter 4

Implementation of a Realistic Case Study

4.1 Introduction

This chapter verifies the proposed ABMS simulation model using a realistic building construction project. It first discusses the case study in terms of location, size, duration, and site operations. It then provides details on the ABMS simulation model implementation followed by a discussion of the model's outputs. Finally, sensitivity analysis is presented of the simulation outputs.

4.2 Earthmoving Case Study

The case project is a new centre for Living and Learning at McMaster University. The building is a 12-story, 359,000 square-foot student residence, classroom, and activity building in Ontario, Canada. The project site before construction is shown in, Figure 4.1. The building will be home to a 500-bed student residence, new teaching space, student meeting and activity space and the McMaster Childcare centre. The building is an on-campus student residence and will become a hub for students and visitors. The construction of the project consists of two phases: 1) excavation and earthmoving; and 2) building construction. The excavation operations started on April 2017 and finished by July 2017. The construction of the building started immediately after that and is expected to finish in September 2019.

Figure 4.1. Project Site before Construction

In the excavation and earthmoving phase, it is required to excavate an area of about 61 m width x 60 m length x 10 m depth resulting in a total volume of 36,600 m^3 of earth to be moved, Figure 4.2. These operations involved 20 trucks (10-12 m^3) and 2 loaders (1-2 m^3). The on-site trucks' speeds were 20 km/h when empty, 10 km/h when loaded, and 5 km/h when on ramp. To adjust position for loading around loaders and for departure, trucks required 1-2 min. Loading one scoop requires 1-1.5 min and loading a full truck requires 5-7 min. A truck requires about 2 hours, ±10 min, to complete one cycle of loading, hauling, dumping, and returning for another load, as shown in Table 4.1. Operation hours were 8 h/day and 5 days/week. This phase was accomplished within 3 months period.

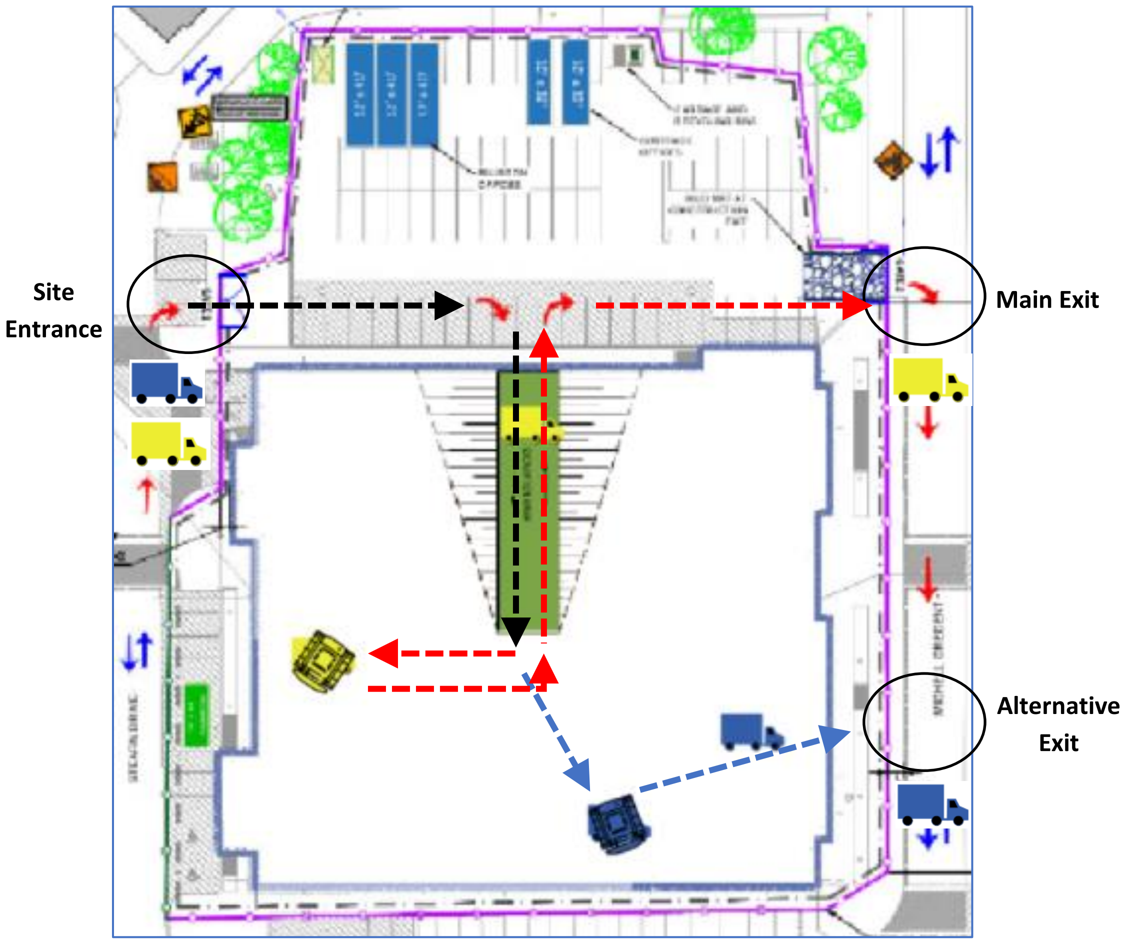


Figure 4.2. Excavation Site and Truck Routes

Table 4.1. Excavation: Equipment Information

	Number	Capacity	Loading Time	Positioning Time	Loading Cycle Time	On-site Speed		
						Empty	Loaded	On-ramp
Trucks	20	10-12 m^3	5-7 min	1-2 min	2 h	20 km/h	10 km/h	5 km/h
Loaders	2	1-2 m^3	1-1.5 min	-	-	-	-	-

The main objective in earthmoving operations is to improve equipment efficiency, productivity, and safety (Cheng et al. 2011). These operations typically fall on the critical path of construction projects and are lengthy in duration. They involve prohibitive delay and accidents costs and rely mostly on utilizing expensive and large fleet of equipment such as bulldozers, trucks, and loaders. Hence, accurate planning of earthmoving operations is crucial to project success (Jabri and Zayed 2017; Vahdatikhaki et al. 2017).

Due to the cyclic nature and type of tasks involved in earthmoving operations, simulation is considered a suitable and valid approach to for planning and analyzing their productivity and cost (Jabri and Zayed 2017). Discrete-event simulation (DES) has been used extensively in the construction simulation industry including earthmoving simulation. However, DES has some limitations. For instance, handling site space constraints and conditions such as congestion, proximity, and access are difficult to model as they do not represent work activities (AbouRizk 2010; Jabri and Zayed 2017; Pradhananga and Teizer 2014). Such limitations often lead to inaccurate productivity and equipment utilization estimates. For these types of problems, the ABMS technique (with its autonomous agents) has highest potential (Zhou et al. 2009).

Most previous efforts that utilized ABMS in earthmoving modelling, however, do not involve agents with decision-making capabilities, problem-solving capabilities, or agents' interactions; which is the most powerful features of ABMS. For example, Jabri and Zayed (2017) represented agents' interaction by an agent (loaders and spotters) controlling the waiting time of another agent (trucks); which is not a utilization of agents' interactions. In the context of ABMS, interactions between agents such as communication, movement and contention for space, and the capability to respond to the environment influence their behaviours and decisions (Macal and North 2010), which are the features utilized in the developed ABMS model of this research.

4.3 ABMS Implementation

This section presents the ABMS model developed for simulating the earthmoving operation at the case study site. To get the case study data, a site visit was carried out at the project site and several consultation sessions were held with project consultants to verify the data and get feedback on model performance. The model was developed by customizing the developed NetLogo model to the case study at hand. On site, the first phase of earthmoving operation involved 10 trucks (11 m^3 capacity) and 2 loaders (1.5 m^3 bucket). The total excavation amount is assumed to be 20,000 m^3. The site (Figure 4.3) has one entrance and the shaded area at the entrance (front of the temporary facilities) is considered a slowdown area (obstacle O1), where trucks have to move slowly (less than the max speed on site of 10km/hr). The site also has two exits (Figure 4.3), as follows:

- **Main exit:** to use it, a truck has to go down the ramp, get loaded, and return back to take the ramp (thus making the ramp a danger zone), then proceed to the main exit. An aggressive driver would take this risky route since it leads to a shorter distance to the dump area (about 2 hours, ±10 min, to complete one cycle of loading, hauling, dumping, and returning for another load); and

- **An alternative exit:** to use it, the truck leaves the site immediately to this exit after being loaded, with no need to go up the main ramp, thus avoiding the danger zone. An avoider driver may take this route, which leads to a bumpy route that leads to a lengthier work cycle of about 2.25 hours (±15 min).

The site in Figure 4.3 visualizes the two types of obstacles on the site:

- Slowdown area close to the entrance;
- Danger zone represented by the ramp.

4.3.1 Model Inputs

To facilitate an easy and quick modification and multiple scenario simulation, the model accepts two input methods of variables: models' interface and CSV files. The positions of the two loaders used in the earthmoving operation, the site entrances used by the two groups of trucks (Aggressive: Team 1; and Avoider: Team 2), and site exist are specified in two CSV files. The first one, Figure 4.4, is for determining the locations (coordinates) of the two loaders. The second CSV file, Figure 4.5, is dedicated to specify the locations of entrance and exit for each team. On the other hand, variables (inputs) such as: number of trucks, loader capacity, loading locations, dumping duration, etc. are changed using input boxes in the model's customized interface (bottom of Figure 4.3), to facilitate data entry and sensitivity analysis. For each team, aggressive and avoider, these inputs include:

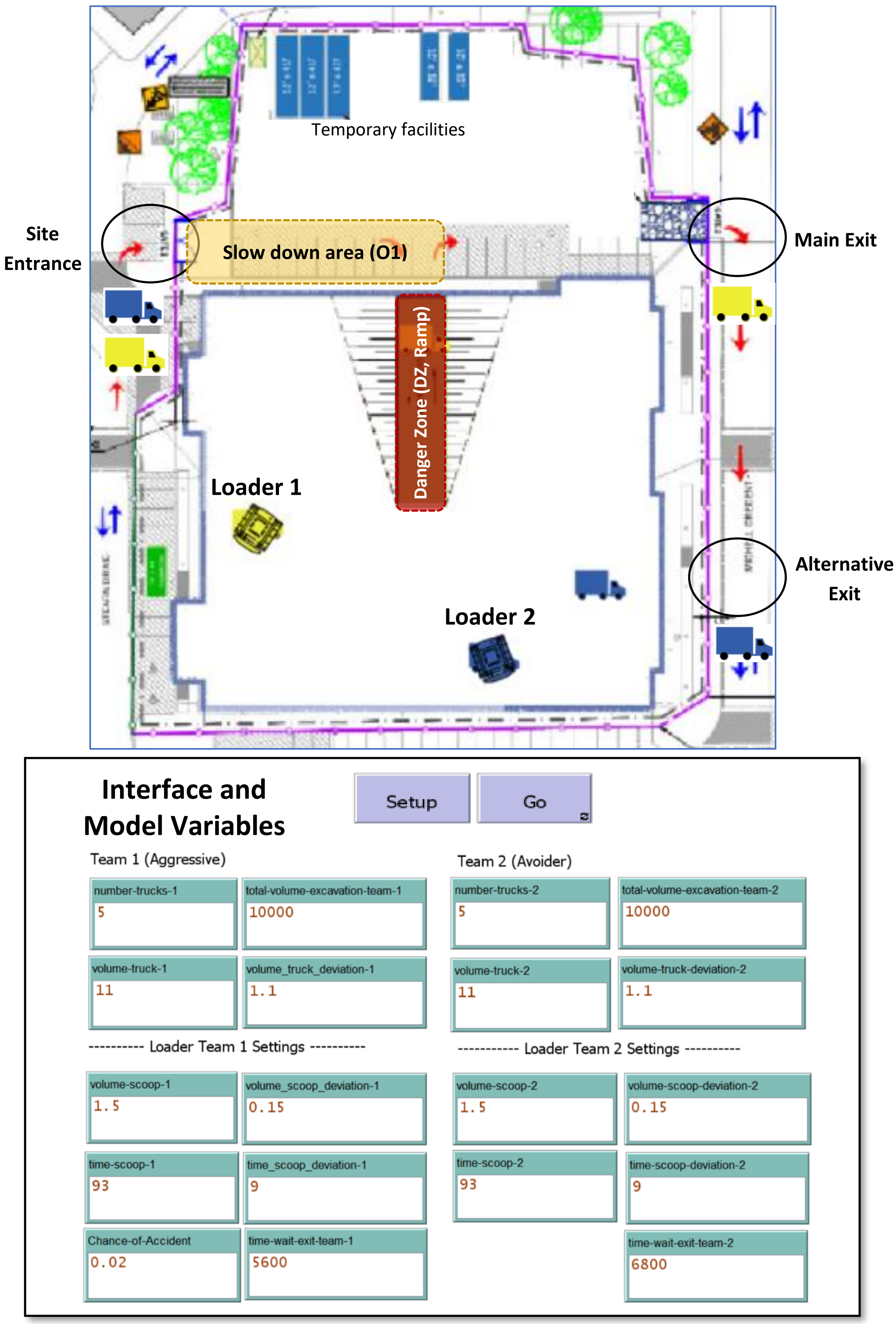


Figure 4.3. Simulated Site and Model Variables

- Number and capacity of trucks – 5 trucks, 11 m^3 capacity each;
- Capacity of one loader's scoop – 1.5 m^3;
- Duration of loading one loader's scoop (in ticks) – 93 ticks;
- Aggressive trucks round-trip duration to dumping site (in ticks) – 5,600 ticks;
- Avoider trucks round-trip duration to dumping site (in ticks) – 6,800 ticks
- For only aggressive trucks, the probability of breakdown (or accident) – 2%

	A	B	C	D	E
1	machine	name	x	y	group
2	1	John	3	-10	2
3	2	Robert	-6	-5	1

Figure 4.4. Input Sheet for Loaders' Coordinates

	A	B	C	D	E	F	G	H
1	Entrance X T1	Entrance Y T1	Exit X T1	Exit Y T1	Entrance X T2	Entrance Y T2	Exit X T2	Exit Y T2
2	-11	3	13	10	-11	3	13	-10

Figure 4.5. Input Sheet for the Entrance and Exit Coordinates

To define the routes for the two groups (Aggressive and Avoider), other interface elements were built as shown in Figure 4.6, showing each segment of the route along with the relative speed associated with each segment (depending on grade and other factors). The bottom of Figure 4.6 also shows interface elements to show intermediate information during the simulation such as elapsed time and the remaining amount of material.

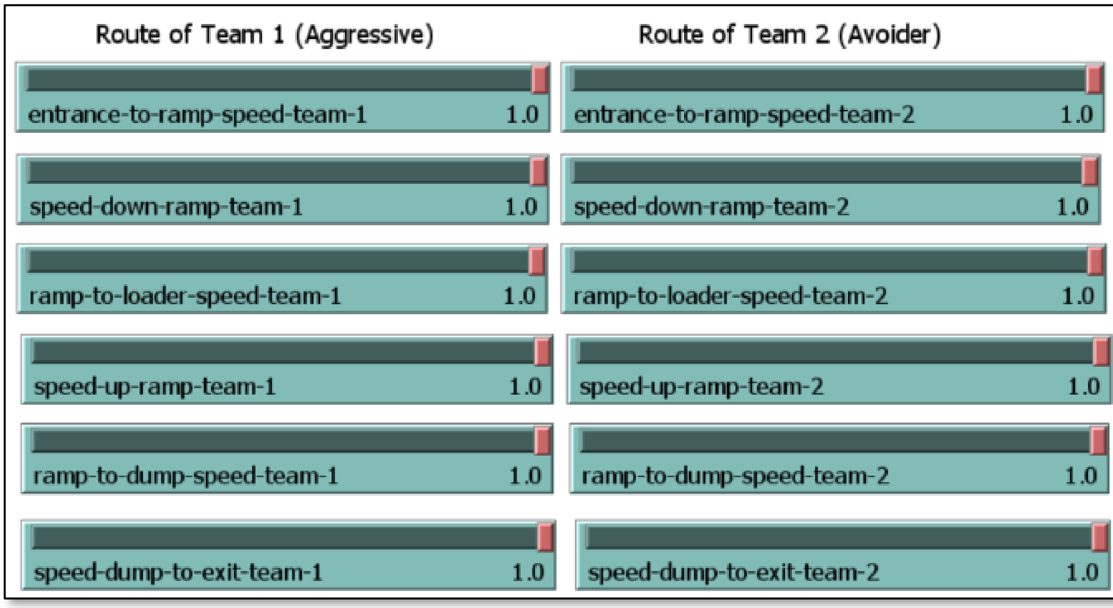


Figure 4.6. Defining Route Sections and Speeds

4.3.2 Simulation and Outputs

During simulation, the model simulates a truck passing 1 patch in 1 time unit (tick). Considering the site dimensions and the maximum speed within site, the grid size (patch) was selected to be 3.55 m x 3.55m. Accordingly, 1 tick in the model equals to 1.28 real seconds. Truck drivers get to choose their driving speed within a range of ±10% of the speed limit and which exit and loader to use. From the entrance to the bottom of the ramp, truck drivers use the assigned driving paths. Within the excavation area, trucks have complete freedom of movement to reach the loader, avoid hitting other trucks, waiting for a truck to load, go down the ramp, and head towards either exit. In the current stage of model development, the model simulates the excavation operations and trucks' movements without considering or incorporating a traffic management plan. In this case study also, no workers are created in the simulation and only the trucks are involved. Incorporating both trucks and workers and their interactions within the simulation will be considered in future work. Along the simulation, various outputs are monitored on the screen (Figure 4.7) including simulation time, and the quantity of material moved by the different groups of trucks.

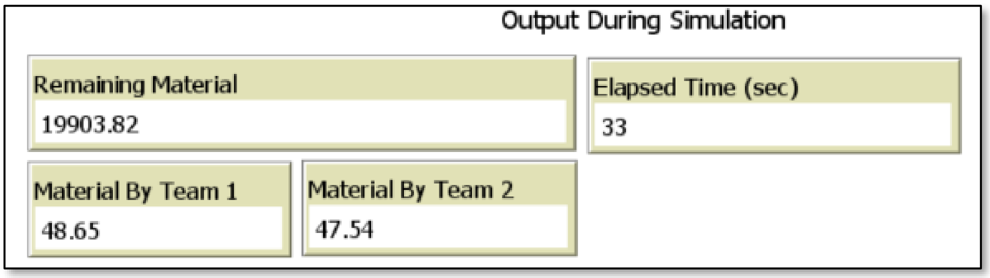


Figure 4.7. Monitored Outputs during Simulations

The results of 10 simulation runs show that the average daily production of the aggressive group was 227 m^3/day (in case no accident happens), as compared to the 191 m^3/day of the avoider group. Based on the results of a number of simulations, the accident/injury potential of the aggressive group (considered 50% of trucks, to be conservative) was 1 in 108 days, which is beyond but not far from the duration of the operation. With a 5-day working week, the average duration of the job was 65 days (when no accident happens) and 76 days with an accident (a truck is removed from the accident time till end of simulation).

With the accident potential being high, a new experiment was carried out to present the project manager with a solution that would dramatically reduce this potential, thus proving the usefulness of the model. In this experiment, the main exit is closed to avoid having any trucks going up the ramp, thus removing the danger zone. Only the alternate exit was used in the simulation. The results of this scenario show that a total duration of 70 days is required to complete the project with a daily production rate of 402.6 m^3/day. This result shows that with some site rearrangement, accident potential is avoided at an expense of about 7% (5 days out of 70) of productivity time (and cost).

4.3.3 Sensitivity Analysis

The obstacle distance on the trucks' path represents 1% of the total truck trip time. Yet, the model was capable of capturing the effect of this obstacle on the trucks' productivity. Further investigation was carried out by trying different values for the speed factor analyze the effect of the obstacle on the trucks' daily production. As shown in Figure 4.8, the results show that speed factor values from 1 to 0.5 resulted in a semi-linear reduction in productivity, followed by exponential reduction under speed factor values below 0.5.

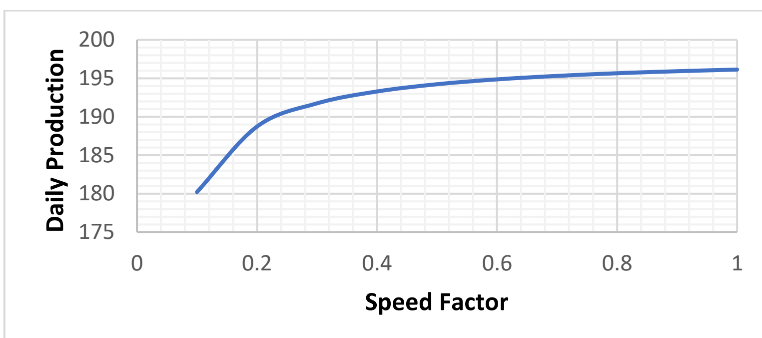


Figure 4.8. Obstacle Sensitivity Analysis

In another experiment, the model was used without considering any obstacles, to conduct sensitivity analysis by varying the number of trucks and number of loaders. As shown in Figure 4.9, the analysis results show that no more than 18 trucks should be used. Any larger number of trucks will have almost no effect on production. On the other hand, 2 loaders is the optimal number to be used for this project as the use of more than two loaders will not improve the production rate.

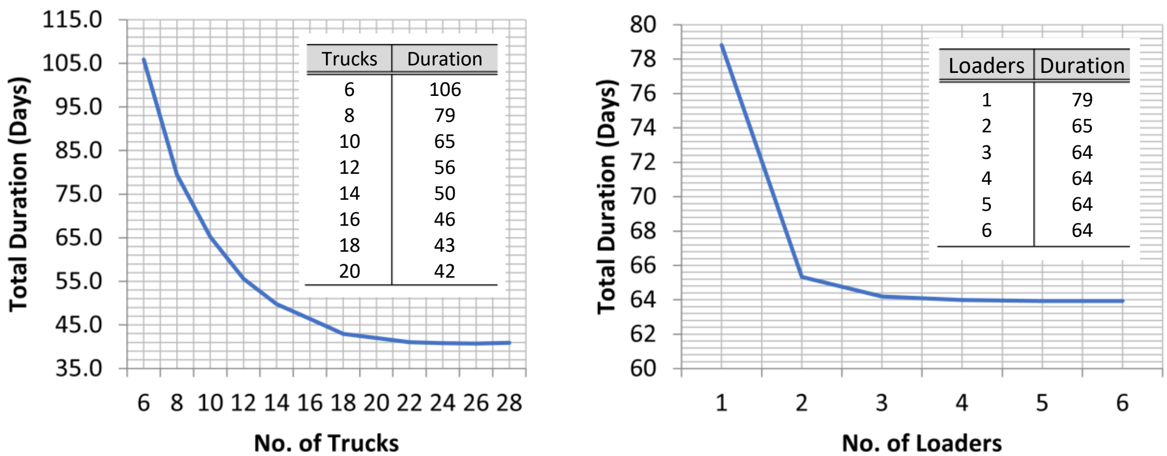


Figure 4.9. Sensitivity Analysis Results

4.4 Conclusions

This chapter presented the implementation of the proposed ABMS simulation model on the earthmoving operation of a realistic building construction project. This chapter illustrates the flexibility and usability of the developed ABMS model which is shown in the smooth shifting from simulating workers, presented in the hypothetical case study of chapter 2, to simulating equipment (earthmoving trucks and loaders). Simulating alternative on site trucks' routes and exits also illustrates the practicality of the developed input methods that facilitates quick modification and multiple scenario simulation.

Chapter 5

Agent-based Site Layout Optimization

5.1 Introduction

This chapter presents the implementation of a GA optimization model within the agent-based simulation model to optimize construction site layout plans. It first discusses the set up of the GA optimization model including its objective function, population, and reproduction mechanisms. Then, it provides details about the construction phase of the case project. After that, it discusses how the model searches and finds the optimal site plan (i.e., defines the best locations for the site temporary facilities) based on the productivity and safety outputs of the simulation model. Finally, sensitivity analysis of the outputs is presented.

5.2 Genetic Algorithm (GA) Optimization Model

Genetic Algorithms (GAs) employ a random yet directed search for finding a near-optimal solution. Typically, GAs simulates natural evolution by representing an optimization problem as a species that need to evolve its population following a survival of the fittest strategy. Each population member is represented in the form of a string (or chromosome) with a number of genes that represent the variables involved. Each chromosome (member in this species) represents a candidate solution (i.e., a candidate site layout) that competes with other population members over millions of cycles of evolution until the most-fit solution emerges. Along the process, each member is evaluated against the objective function, which determines the fitness of each chromosome. The offspring generation process among the population members takes place by crossover or mutation operators to evolve new members. In crossover, an offspring is produced by a random exchange of information between two parent chromosomes. This is by far the more common process. The mutation process is conducted by randomly selecting a chromosome from the population and arbitrarily changing some of its information. To simulate the natural process of "survival of the fittest", an offspring may, if it is more fit, replace other chromosomes in the population. Usually, the reproduction process is repeated many times to generate a large number of offspring generations in which the population is enhanced and an optimum chromosome is found (Hegazy and Elbeltagi 1999; Mawdesley et al. 2002).

The proposed framework integrates the developed agent-based simulation model (descried in Chapter 3) and a GA optimization model that searches for the optimal site layout configuration that maximizes productivity and minimizes safety concerns. In the following sections, the GA model setup is discussed. This is followed in sections 5.4 and 5.5 by a detailed description optimization results and sensitivity analysis results, respectively.

5.2.1 Model Setup

The proposed GA model represents the construction site by a coordinate system with the centre of the area as its origin (x_0, y_0) and the opposite corners are represented by the two points (x_{max}, y_{max} and x_{min}, y_{min}), Figure 5.1. The agent-based simulation model acts as the fitness function evaluator for any site configuration chromosome (with is unique positions of the temporary facilities) and measures its productivity (number of trips) and accident potential. Through thousands of GA cycles, the optimization model searches for the optimum chromosome that defines the best locations of all facilities.

Seven possible locations are considered for allocating the required temporary facilities, Figure 5.8. First, the simulation model reads and imports the coordinates of these locations from a csv file, Figure 5.2. Then, the optimization model controls the simulation model, reads its inputs, and manipulate its parameters. For the purpose of facilitating the integration of the two models, the simulation model was built with functions that were coded to provide the optimization model with the needed parameters and objective function in the way that allows it to perform its function. Implementing GA optimization involves four primary steps: (1) setting the chromosome structure, (2) deciding the objective function, (3) generating an initial chromosome population, and (4) selecting reproduction mechanisms. Each of these steps is discussed in detail in the following subsections.

5.2.2 Setting the Chromosome Structure

The chromosome structure is a string of elements (Genes), each corresponding to a facility location (L_i). The chromosome length is determined by the total number of facilities, Figure 5.3. Each chromosome represents a possible site layout. It is represented as follows:

$$[(L_1),(L_2),(L_3),\dots\dots\dots\dots\dots\dots(L_n)\ ] \qquad (5.1)$$

where L_i is the Location ID of facility i , and n is the total number of temporary and fixed facilities. It is important to mention that before any of the chromosomes is used in the GA operations (crossover or mutation), it is tested for feasibility (i.e., no two facilities on the same location). Also, if an offspring is generated, it is tested for feasibility. If it fails, a new offspring is generated in the same cycle.

As shown in Figure 5.3, facility ID's 1 to 7 have the option of being allocated in location ID's 1 to 7. In this manner, each combination of allocating the facilities in these locations represents a chromosome.

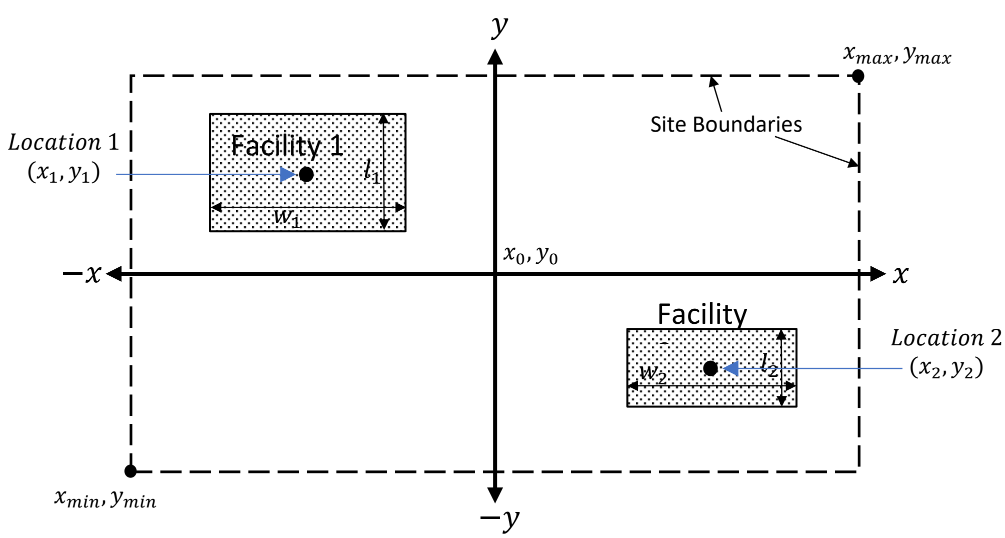


Figure 5.1: Coordinate System Representation of Construction Site

	A	B	C
1	id	x	y
2	1	-20	-45
3	2	-20	45
4	3	-20	-90
5	4	30	-45
6	5	30	90
7	6	30	45
8	7	-20	90
9	8	30	-90

Figure 5.2. Input File for the Coordinates of Available Facilities' Locations

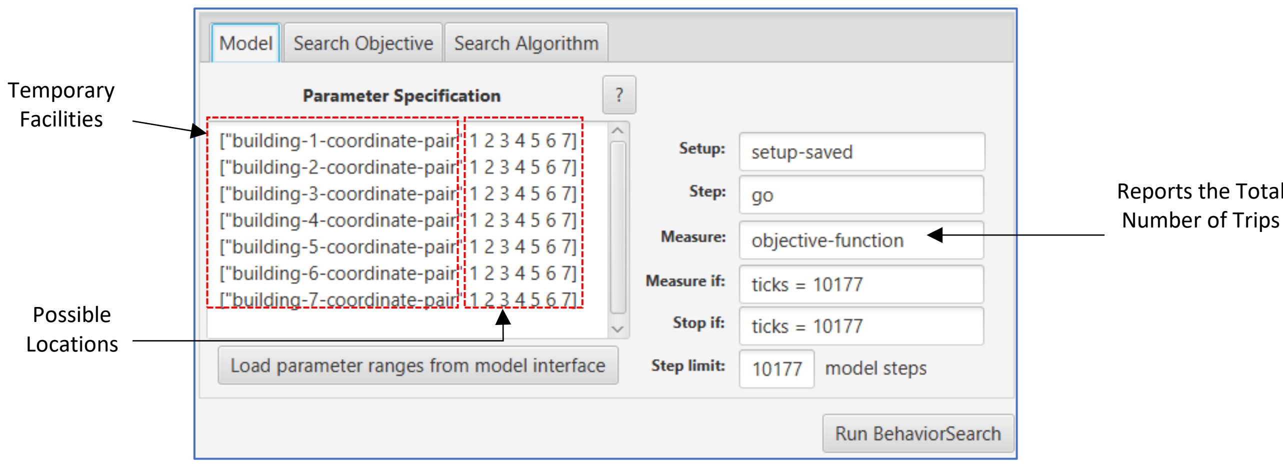


Figure 5.3. Setting Up Parameter Ranges and Chromosome Structure

5.2.3 Objective Function

The ultimate goal is to find the optimal locations of site facilities. Accordingly, the framework optimizes the facilities locations by simulating the operations of one working day (the day with highest activity rate) in which only the productive operations are simulated. The workers' movement paths were determined within the simulation model (discussed in Chapter 3) in which the shortest path between each two locations and for each worker types are chosen and assigned. Thus, the objective function is maximizing the total number of trips (maximum productivity). In this matter, the volume of work flow between work locations is considered. The objective function that evaluates the performance (fitness) of a candidate layout (a chromosome) is formulated as follows:

$$\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} T_{ij} \tag{5.2}$$

where n is the total number of fixed and temporary facilities and T_{ij} is the number of trips between facilities i and j.

The objective function represents the total number of trips associated with a given site layout (which is obtained from the simulation model), taking into account the effect of site obstacles, danger zones, workers' behaviors, and crowded areas while calculating the total number of trips. As such, the optimization objective is a direct function of all the site characteristics, obstacles, accidents, and behaviours. Maximizing this objective function is required in order to arrive at the layout that results in the highest productivity, safety, and work flow, which is performed by finding the optimal locations of the facilities.

5.2.4 Generating an Initial Chromosome Population

After setting up the chromosome structure and objective function, a population of possible site layout solutions (parent chromosomes) needs to be generated. Population size is an important factor that affects the solution quality and the processing time. Larger population size increases the likelihood of obtaining a global optimum; however, it also increases the processing time (Hegazy and Elbeltagi 1999). In the current model, the population size was set to be 100 members,

Figure 5.4. Once the population is generated, the fitness of each candidate site layout (each chromosome) can be evaluated against the objective function, equation (5.2). The workers' speed and the tasks durations are normally distributed with a 10% standard deviation. Therefore, it is required to perform more than one simulation run for each layout (each member of the population) in order to get representative results. A convergence test was performed to determine the appropriate number of simulation replicates. As shown in Figure 5.6, the test show that ten replicate runs are enough to get a convergence (representative outputs). Then, each member of the population is candidate for reproduction by either crossover or mutation as explained in the following section.

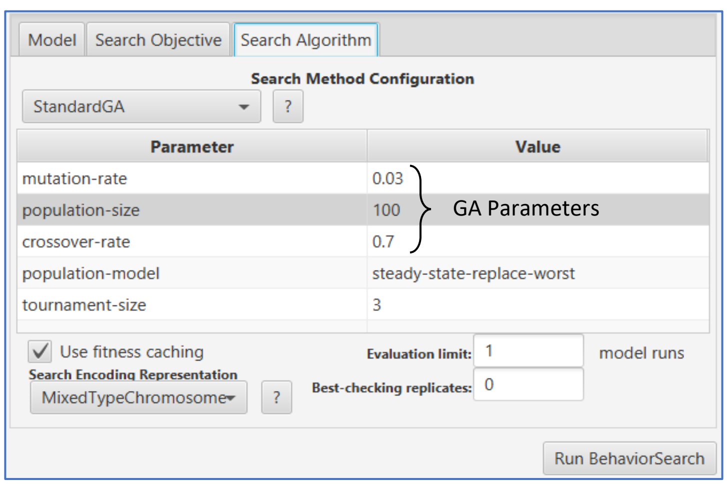


Figure 5.4. GA Parameters

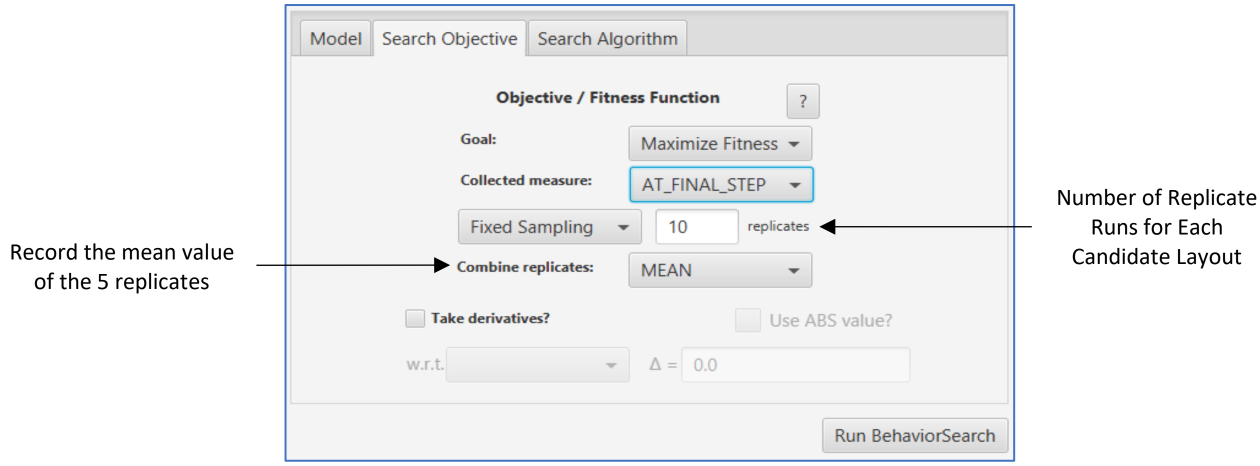


Figure 5.5. Additional GA Settings

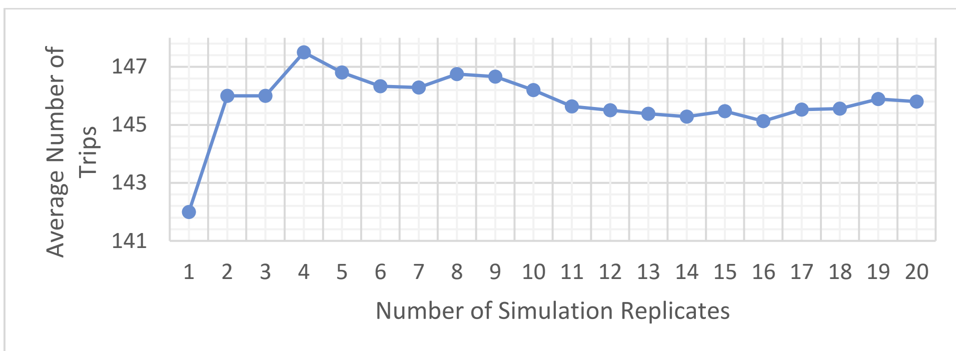


Figure 5.6. Convergence Test

5.2.5 Selecting a Reproduction Mechanism

In the reproduction process, offspring layouts are produced by either crossover or mutation operators. This process is considered the most important part of the GA and the performance of a GA is influenced mainly by these two operators. In crossover, parent layouts $(P^1, P^2, P^3, \ldots \ldots P^t)$ are randomly selected, Figure 5.7. Then, randomly exchanging elements values (location IDs) between each two parent layouts. For example, let $P^1 = [(L_1), (L_2)]$ and $P^2 = [(L_3), (L_4)]$. This means that there are two facilities, and in parent P^1 their locations are (L_1) and (L_2), respectively. If the location of the first facility (L_1) is randomly selected for exchange, the offspring layout will be $O^1 = [(L_1), (L_4)]$. In this model, crossover rate is set to be 0.7, see

Figure 5.4.

On the other hand, mutation is conducted by generating a random number and exchanges it with a location that is randomly selected from a randomly chosen parent so that the original position of a facility is changed. The importance of the mutation operator is that it can break stagnation and avoiding falling into a local optimum (Hegazy and Elbeltagi 1999). For the example above, if L_2 is a randomly selected location to be exchanged with the location of the second facility of parent P^2, then the offspring layout will be $P^2 = [(L_3), (L_2)]$. Mutation rate is set to be 0.03. If the operators generated an invalid offspring layout that involves the allocation of two facilities in the same location, then this layout will not be simulated, will be given a zero number of trips (zero-fitness value), and will be discarded. In this manner, only the valid offspring layouts will be simulated which will reduce the run time and improve the efficiency and quality of the optimization outputs.

After generating the offspring layouts, the simulation model will be used to obtain their work flow evaluations (number of trips associated with each offspring layout). Then, their fitness will be evaluated against the objective function. If the offspring layout is more fit than that of the least-fit layout in the population, then it will replace it; otherwise, this offspring layout will be discarded. This process is continued until a pre-specified maximum number of generations are reached. In this model, the total number of searches was set to be 10,000 including the invalid chromosomes (layout combinations).

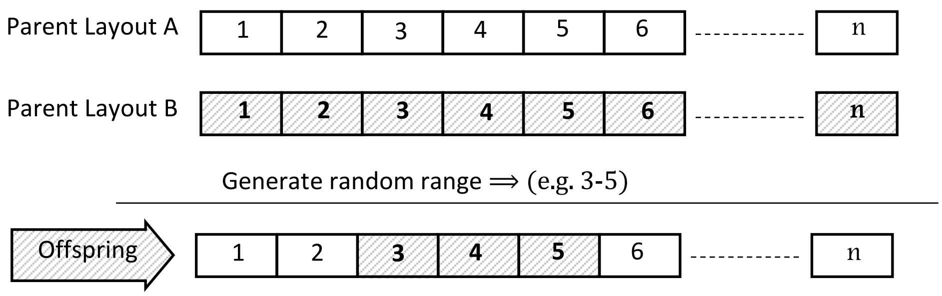


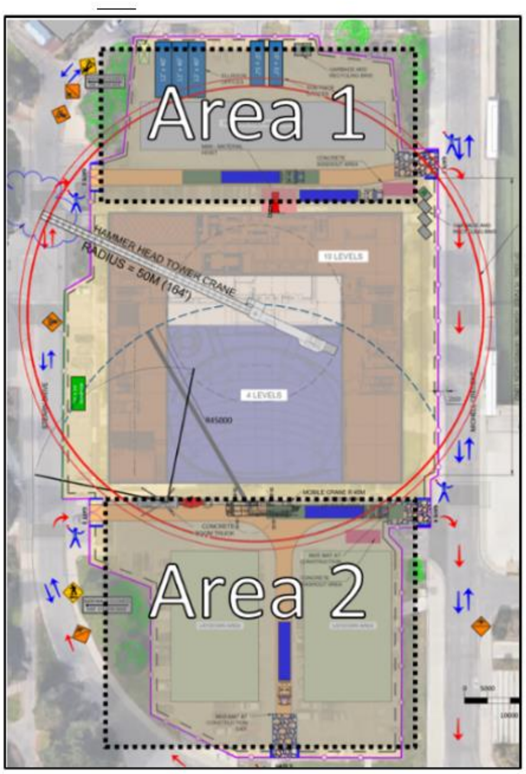
Figure 5.7. Crossover Operation to Generate Offspring

5.3 Case Study Project

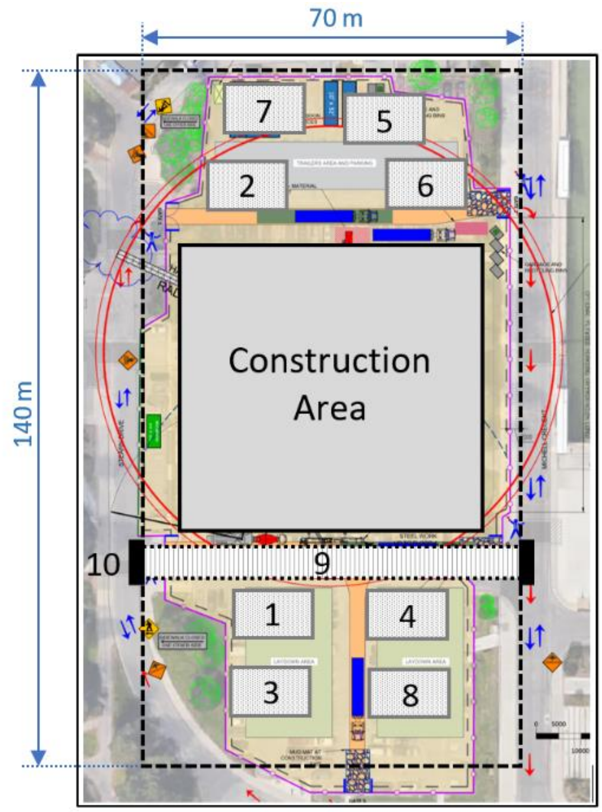
The case study project is the same centre for Living and Learning project discussed in Chapter 4. The site layout needed is for the construction phase of the building itself after completion of all earthwork. The operations on site involves 61 workers with different types, tasks, and work locations. Table 5.1 lists the activities' information including durations and workers' start and destination locations. The constructed building is located in the centre of the site, as shown in Figure 5.8 (a), with an area of 2,500 m^2 (50 m x 50 m). The project involves the construction space and 10 facilities, 7 movable and 3 fixed, Table 5.2. Seven locations are available for allocating these movable facilities, as shown in Figure 5.8 (b). This means that there are more than 800,000 possible Layout solutions and more that 5,000 if a location is restricted to contain only one facility at a time. It would be impractical to try all these possible solutions and, therefore, GA optimization is needed to solve such problem. The site contains 3 types of obstacles: O1, O2, and DZ with areas of 160 m^2, 200 m^2, and 180 m^2, respectively. The obstacles are located around the main building as shown in Figure 5.9.

Table 5.1. Workers and Facility Information

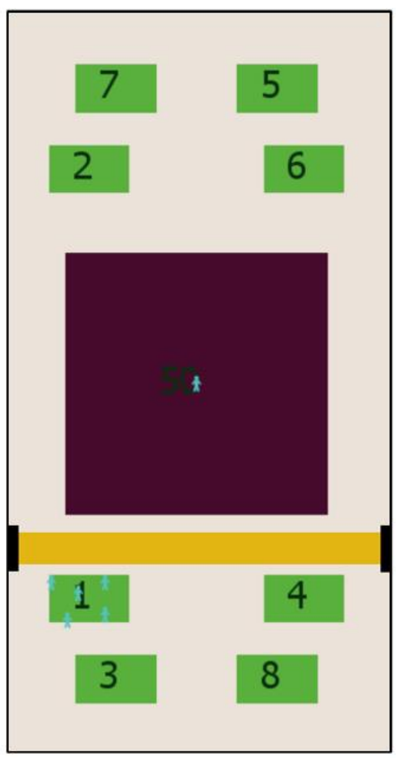
Source Facility		Groups	Working Time (h)	Destination Facility		Working Time (h)	Number of Workers
ID	Name			ID	Name		
1	Carpentry Shop	1A	6	MB	Main building	2	12
		1B	2	MB	Main building	6	12
2	Scaffold storage yard	2	2	MB	Main building	3	4
3	Material warehouse	3	1	8	Long term laydown yard	1	4
				1	Carpentry Shop	1	
				4	Rebar fab/storage yard	1	
4	Rebar fab/storage yard	4A	6	MB	Main building	2	8
		4B	2	MB	Main building	6	8
5	Sampling testing lab	5	3	MB	Main building	1	4
6	Office	6A (project manager)	2.5	MB	Main building	1	1
		6B (supervisors)	1	MB	Main building	2.5	4
				4	Rebar fab/storage yard	1	
7	Safety Office	7	2	MB	Main building	2	4
				4	Rebar fab/storage yard	2	



a) Site Map



b) Possible Locations



c) Model

Figure 5.8. Available Area for Allocating Facilities

Table 5.2. Site Facilities

Facility ID	Facility Name	Facility Type
MB	Main Building	Fixed
1	Carpentry Shop	Movable
2	Scaffold storage yard	Movable
3	Material warehouse	Movable
4	Rebar fab/storage yard	Movable
5	Sampling testing lab	Movable
6	Office	Movable
7	Safety Office	Movable
8	Long term laydown yard	Fixed
9	Road	Fixed
10	Gates	Fixed

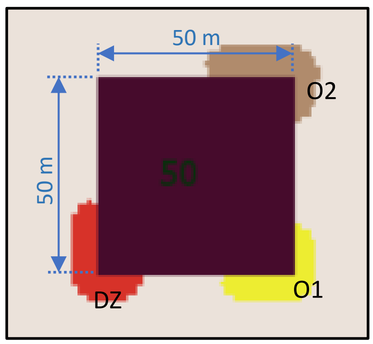


Figure 5.9. Locations of Site Obstacles

5.4 Optimization Results

After setting up both the simulation and optimization models, the search for the optimal site layout plan can start. The objective function maximizes the total number of trips for one working day for all site operations and workers. With two types of workers, Avoiders and Aggressive, and to examine the effect of obstacle on productivity and work flow, the framework has been used to optimize the site layout by simulating only avoider workers, only aggressive workers, and both worker types (50% avoiders and 50% aggressive). In this manner, the two types of behaviour around obstacles can be compared and analyzed.

The optimal plan for the “Avoiders only” experiment was facilities 1, 2, 3, 4, 5, 6, 7 in locations 4, 2, 3, 1, 5, 6, 7, respectively, with 143.2 total number of trips. The worst plan for this experiment was facilities 1, 2, 3, 4, 5, 6, 7 in locations 2, 1, 4, 3, 6, 5, 7, respectively, with 134 total number of trips. For the “Aggressive only” experiment, the optimal plans were facilities 1, 2, 3, 4, 5, 6, 7 in locations 4, 7, 6, 1, 2, 3, 5, respectively, with a total number of trips of 137.6. The worst plan was facilities 1, 2, 3, 4, 5, 6, 7 in locations 2, 1, 4, 3, 6, 7, 5, respectively, with 129.6 total number of trips. On the other hand, the “50% - 50%” produces 142.4 total number of trips and the optimal plan was facilities 1, 2, 3, 4, 5, 6, 7 in locations 4, 2, 3, 1, 5, 6, 7, respectively. AS show in Figure 5.10, the “Avoiders Only” experiment produced higher number of trips than other experiments. The “50% - 50%” experiment also produced high number of trips but not as high as the trips of “Avoiders Only” experiment.

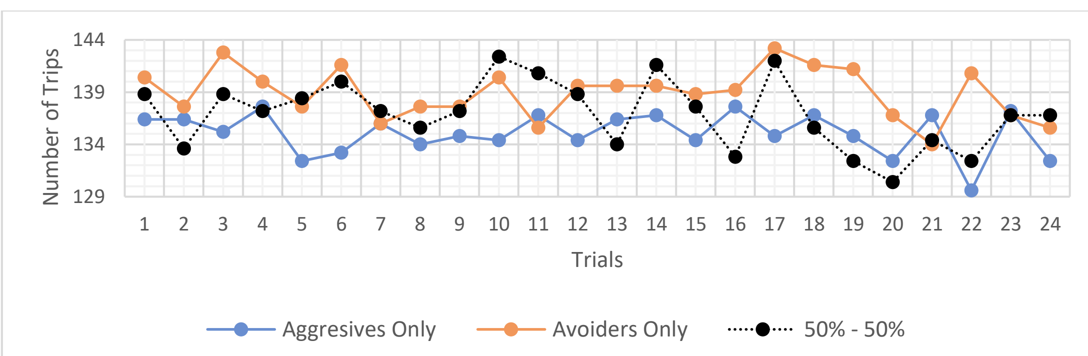


Figure 5.10. Comparison of Results

5.5 Sensitivity Analysis

This section provides project managers with further useful experimentation with the developed framework. It presents the analysis and examination of the effect of obstacles' sizes and shapes on workers' performance and the overall site productivity. The importance of such analysis is to help the decision maker establish policies for site work. This includes:

1. Removing a certain obstacle (with extra cost);
2. Enforcing strict policy to avoid aggressive behaviour; Or
3. Put no restrictions on workers.

In this analysis, four cases were considered:

a. ***Case 1***: reduce obstacle sizes 50% and keep their original shapes, Figure 5.11 (a);
b. ***Case 2***: enlarge obstacle sizes 150% and keep their original shapes, Figure 5.11 (b);
c. ***Case 3***: reduce obstacle sizes 50% and change their shapes, Figure 5.11 (c);
d. ***Case 4***: enlarge obstacle sizes 150% and change their shapes, Figure 5.11 (d).

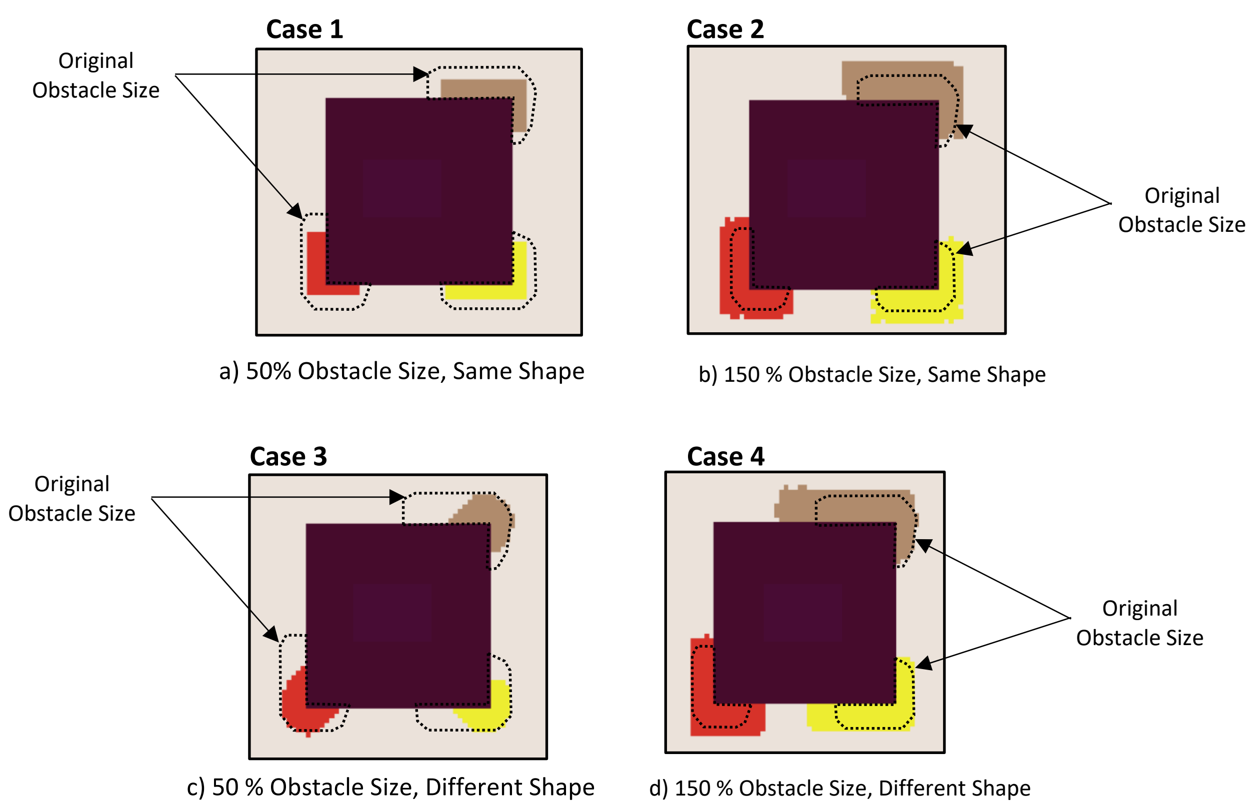


Figure 5.11. Cases with different Obstacle Sizes and Shapes

First, the site layout was optimized considering that there are no obstacles on site. The optimal layout was facilities 1, 2, 3, 4, 5, 6, 7 in locations 4, 5, 3, 1, 2, 6, 7 with total trips of 148. After that, the optimal layout was used to conduct sensitivity analysis to examine the effect of obstacles' sizes and shapes as described earlier. Similar to the previous section, for each case the "Avoider workers only", "Aggressive workers only", and "50 % of each worker types" are simulated. Table 5.3 lists the productivity assessment results for each case. The results of Case 1 show that the total number of trips is 139.8 and 138.2 for the "Avoider workers only" and "Aggressive workers only", respectively. The results of this case show the project manger that having obstacles even with 50 % their original size will still reduce site productivity and, accordingly, the project manager should recommend option 1, removing obstacles.

Table 5.3. Effect of Different Obstacle Sizes and Shapes on Productivity

Workers' Type	Analysis Types	Number of Trips
-	NO Obstacles Case	148.0
Avoider Workers Only	100% Obstacle Size	138.4
	Case 1	139.8
	Case 2	137.6
	Case 3	144.2
	Case 4	136.0
Aggressive Workers Only	100% Obstacle Size	135.2
	Case 1	138.2
	Case 2	133.0
	Case 3	139.5
	Case 4	135.5

In case 2, obstacles have greater effect, compared to case 1, on both avoider and aggressive worker groups. The avoider workers achieved 137.6 trips and the aggressive workers achieved 133 trips. The results of this case clearly show that the obstacles need to be removed, Option 1, even if the removal cost is high. Case 3 shows that the avoider workers achieved 144.2 trips; while the aggressive workers had 139.5 trips. However, the aggressive workers have a higher improvement compared to other cases. For this case, the project manager should recommend option 1, removing obstacles. If the obstacles' removal cost is high and considered more important, or will have a higher cost, than meeting the project's deadline, the project manager may recommend option 2, enforcing strict policy to avoid aggressive behaviour. Further investigation about the obstacles' effect on the total project duration is recommended in this case. In case 4, the obstacles have a significant effect on both worker types. The avoider workers achieved 136 trips and the aggressive workers achieved 133.5 trips. Similar to case 2, it is clearly that the obstacles need to be removed, Option 1.

The analysis in this section shows that both behaviours, avoider and aggressive, achieved good performance when having the obstacles of case 3. Also, the results of both worker groups in this case have achieved better productivity than of other cases, especially the aggressive workers. On the other hand, the obstacles of case 1, which have the same obstacles' sizes of case 3 but different shapes, have reduced the site productivity and required obstacle removal. Both case 2 and 4 significantly affected the site productivity and required obstacles removal. However, the obstacles in case 2 had a greater effect on the aggressive workers; while case 4 obstacles had a greater affect on the avoider workers. This is due to the change in the obstacles' shapes between the two cases.

A limited form of validation was carried out to check the usefulness and practicality of the developed framework by presenting the system and its results to one of the project managers who were involved in the earth-moving case study. His feedback was very supportive and confirmed the framework's accuracy in representing the workers' behaviors, site obstacles, and the overall site operations. The framework developed in this research can help project managers optimize construction site layouts considering actual site obstacles and workers' behaviours. In addition, the analysis in this section shows how the framework can be a valuable tool that can help investigate the effect of various site obstacles and workers' behaviours on productivity and work progress. Accordingly, informed decisions that can reduce progress delays and improve productivity and safety can be made.

5.6 Conclusions

This chapter presented the implementation of the developed framework on optimizing the site layout for the construction phase of case project, the new Centre for Living and Learning. It shows the integration of the GA optimization model with the agent-based simulation model. First, it presented the case project data and site characteristics. Then, it discussed the GA optimization model's parameters, objective function, and reproduction mechanism. After that, the implementation of the framework and the results are discussed. Different types of behaviours around obstacles are used and compared. The chapter also examines the effect of obstacles on the overall site productivity by conducting sensitivity analysis that considers several different obstacles' sizes and shapes. Based on the analysis results, project managers establish policies to remove a certain obstacle (with extra cost), enforce strict policy to avoid aggressive behaviour, or put no restrictions on workers.

The results and analysis presented in this chapter verify the proposed site layout optimization framework. It provided the details of optimizing the site layouts based on real site conditions and characteristics such as workers' behaviors, site obstacles, and danger areas. Accordingly, the framework outputs, optimal site layouts, are expected to be more realistic and more representative to the real problem. Decision makers can use this information to suggest a more informed solutions and more accurate problem identification.

Chapter 6

Conclusions

6.1 Summary

This research presented the development and implementation of a framework that combines agent-based simulation with GA optimization for optimizing construction site layouts. First, it presents a review of current literature and research developments in site layout planning models and methodologies including their characteristics and limitations. Discrete-event simulation is then presented as a dominant technique for simulating site layout problems. Agent-based simulation is then introduced as a powerful technique with a great potential for modeling construction site layout and performing micro-level simulation and analysis.

As an effort towards improving site layout planning, this research proposes a framework that integrates a site-layout optimization procedure with an ABMS model for micro-level simulation of construction site operations, considering workers' behaviors around site obstacles. To achieve this objective, first, existing site layout and optimization methods were studied to understand the interactions between objects on site, the types of site obstacles, and different workers' behaviors on site. Accordingly, an Agent-Based Modeling and Simulation (ABMS) framework was developed to consider: sizes and locations of site facilities and obstacles; efficient representation of the workers as agents; and the autonomous movements and behaviors of workers around obstacles. Accordingly, it simulates the operation and determines the work productivity and accident potential of any site configuration. The details of developing and implementing the ABMS simulation model involved modeling two workers' behaviors (avoider versus aggressive) around variety of site obstacles and developing behavioural rules for self-determined movement paths, which affect productivity and safety. Two self-determined path methods are introduced, compared, and verified using a hypothetical case study.

The ABMS model was coded in the NetLogo environment with a customized interface developed to easily accept different types of agent groups with each group having unique characteristics such as walking speed, duration, routes, and type of behaviour. Inputs to the model can also be read from a file, and variables such as number of resources, capacity, and duration easily changed from the user interface.

After implementing and validating the ABMS model on a real case study of an earthmoving operation project, it was integrated with a GA optimization model that determines the optimum locations of all temporary facilities on site. The optimization was implemented for the "Centre for Living and Learning" case study. After optimizing the site layout, a sensitivity analysis was performed to examine the effect of obstacle size and shape on the overall site productivity. Based on the analysis results, project managers are able to recommend removing a certain obstacle (at extra cost), enforcing strict policy to avoid aggressive behavior, or put no restrictions on workers.

The results and analysis presented in this research verify the proposed site layout optimization framework. A limited form of validation was carried out to check the usefulness and practicality of the developed framework by presenting the system and its results to one of the project managers who were involved in the earth-moving case study. His feedback was very supportive and confirmed the framework's accuracy in representing the workers' behaviors, site obstacles, and the overall site operations. The ABMS model simulates and assesses site productivity and safety by modeling site objects (e.g., workers and equipment) individually and assessing the effect of their behaviors, which is expected to be an important step towards site layout optimization. The model simulates agents with different types of behaviors that autonomously determine their preferred paths around obstacles. It accepts different site shapes and sizes, obstacle types, obstacle locations and sizes, number of workers, numbers of facilities, and facility sizes. It also accepts different types of agent groups where each group can have its unique characteristics such as walking speed, work durations and routes, and type of behavior. The model provides a practical site and obstacles' input and modification methods, without the need to modify the undelaying code, to facilitate a quick and easy multiple scenario analysis and site characteristics manipulation. The GA optimization model then uses the outputs of the ABMS model to optimize the construction site layouts. In this manner, the framework is expected to provide a more realistic optimized site layouts that takes into consideration the expected site performance and productivity which were formed by simulating the collective behaviors of individual site objects.

This research is expected to provide project managers with an effective tool that considers actual site conditions to help analyze and find the causes and circumstances of productivity loss and accordingly suggest realistic improvement solutions. Considerable effort was spent towards the flexibility and usability aspects of the developed framework. This was illustrated in the smooth shifting from simulating workers to simulating equipment, simulating alternative on site trucks' routes and exit, and the commonly used input and output methods.

6.2 Research Contributions

This research has the potential to improve site layout planning. It contributes to the body of knowledge with the following:

- **Micro-level analysis:** Simulating construction operations at the micro-level by modeling various unique aspects related to construction sites, including: the behaviours of individual site workers; site facilities; and variety of site obstacles, which have direct impact on the overall site productivity and safety.
- **Simulating different behaviors of workers:** Providing a construction operations simulation model that mimics the actual behavior of construction workers in selecting their movement paths on site and around obstacles. This gives the opportunity to optimize facility locations based on real site conditions, not just on their relative distance between each other, which is the common practice in the literature.

- **Different path determination approaches:** Presenting and testing two approaches of modeling agents with different behavior types that autonomously find their path around obstacles on construction sites.
- **A novel layout optimization framework:** Developing a novel agent-based simulation-based optimization for planning construction site layouts.
- **Powerful decision support tool:** Providing a powerful, user-friendly and easy to modify optimization tool for construction site layout planning. It utilizes Microsoft Excel for inputs and outputs to facilitate a user-friendly planning tool. The interface also provides some easy-to-use features in order to try different arrangements such as the locations of facilities and obstacle sizes and shapes.

6.3 Future Research

This research presented an effort on integrating agent-based simulation and genetic algorithm optimization in a framework to optimize construction site layouts. However, with continued research, the framework can be extended to improve the representation accuracy of construction operations and incorporate different optimization techniques. Thus, the following areas are recommended for further study:

- Expanding the present research to study other heuristic and optimization algorithms and techniques such as particle swarm optimization, multi-objective optimization, ant colony optimization.

- Including the modeling of rectilinear facilities to allow for better compaction within tight sites.
- Integrating a procedure for sizing facilities to better utilization of site space and minimize facilities oversizing.
- Considering monetary aspects in optimizing the facilities' locations by considering, for example, equipment operating cost.
- Trying different behavioral and path determination rules.
- Modeling vertical movement of workers; equipment, and materials involved in high rise building projects.
- Linking the present framework to the work schedule to consider the changes in the project's requirements of facilities, workers, equipment, and materials throughout its duration and accordingly provide multiple layouts that accommodate these changes.

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Appendix A

Code for agents' path determination:

Part I: Self-Determined Shortest Path

```
to memorize-path
 let vertex-index find-vertex current-building-id current-destination-building
 ifelse vertex-index != -1[
  let tmp item vertex-index memory
  let route item 0 tmp
  if item 2 route = 0[
   let steps item 1 tmp
   set steps lput patch-here steps
   set tmp replace-item 1 tmp steps
   set memory replace-item vertex-index memory tmp
  ]
 ][
  let tmp[]
  set tmp lput current-building-id tmp
  set tmp lput current-destination-building tmp
  set tmp lput 0 tmp
  let tmp-vertex[]
  set tmp-vertex lput tmp tmp-vertex
  let tmp-steps[]
  set tmp-steps lput patch-here tmp-steps
  set tmp-vertex lput tmp-steps tmp-vertex
  set memory lput tmp-vertex memory
 ]
end
to finish-memorization [origin destination]
 let vertex-index find-vertex origin destination
 if vertex-index = -1[
  show who
 ]
 let route item 0 item vertex-index memory
 let steps item 1 item vertex-index memory
 set route replace-item 2 route 1
 let tmp[]
 set tmp lput route tmp
 set tmp lput steps tmp
 set memory replace-item vertex-index memory tmp
end
```

```
to-report find-vertex [origin destination]
  let result -1
  let i 0
  let flag false
  if not empty? memory
  [
    while [i < length memory and not flag][
      let route item 0 item i memory
      if (origin = item 0 route and destination = item 1 route) or (origin = item 1 route and
destination = item 0 route)[
        set flag true
      ]
      set i i + 1
    ]
  ]
  ifelse flag[
    if i > 0[
      set i i - 1
    ]
  ][
    set i -1
  ]
  set result i
  report result
end

to-report can-use-memorized-path [origin destination]
  let result false
  let vertex-index find-vertex origin destination
  if vertex-index != -1 [
    let route item 0 item vertex-index memory
    if item 2 route = 1 [
      set result true
    ]
    ifelse item 0 route = origin[
      set memorized-path item 1 item vertex-index memory
    ][
      set memorized-path reverse item 1 item vertex-index memory
    ]
  ]
  report result
end

to-report get-first-patch-of-memorized-trip [origin destination]
```

```
  let vertex-index find-vertex origin destination
  let steps item 1 item vertex-index memory
  report item 0 steps
end

to-report get-next-patch-in-trip
  let result -1
  if not empty? memorized-path[
    set result item 0 memorized-path
    set memorized-path remove-item 0 memorized-path
  ]
  report result
end
```

Part I: Forward-Backward Self-Determined Path

```
to clear-exploration
  set agressive-paths[]
  set avoiders-paths[]
  clear-scouts
  ask workers [
    set memory[]
    set using-memory? false
    set memorized-path[]
  ]
  setup-saved
end

to clear-scouts
  ask workers with [name = "ag-scout" or name = "av-scout"][
    die
  ]
end

to setup-scouts
  let all-paths[]
  ask buildings[
    let journey[]
    let origin idb
    let origin-type btype
    ask buildings with [idb != origin][
      ifelse origin-type = "fixed"[
        set journey lput idb journey
```

```
      set journey lput origin journey
    ][
      set journey lput origin journey
      set journey lput idb journey
    ]
    if not check-repeated-paths origin idb all-paths[
      set all-paths lput journey all-paths
    ]
    set journey[]
  ]
]
foreach all-paths[
  a ->
  let start item 0 a
  let goal item 1 a
  let ws[[2 "ag-scout" 25] [1 "av-scout" 95]]
  foreach ws[
    w ->
    create-workers 1 [
      set groupid item 0 w
      set name item 1 w
      set energy stop-criteria
      set home-building start
      set shape "person"
      set size 3
      set color item 2 w
      set speed 1
      set can-be-tired 0
      set can-be-slower 0
      set can-be-injured 0
      let random-location 0
      ask buildings with [idb = start] [
        set random-location patch-here
      ]
      move-to random-location
      set memory[]
      set memorized-path[]
      set in-building? true
      set using-memory? false
      set current-building-id home-building
      set current-destination-building goal
      let random-destination 0
      ask buildings with[idb = goal] [
        set random-destination patch-here
```

```
        ]
        set current-destination random-destination
        face current-destination
        ifelse [pcolor] of current-destination = clr-fixed-facility[
          set fixed-as-destination? true
        ][
          set fixed-as-destination? false
        ]
      ]
    ]
  ]
end

to-report check-repeated-paths [o d path-list]
  let index 0
  let flag false
  while [index < length path-list and not flag][
    let p item index path-list
    if (item 0 p = o and item 1 p = d) or (item 1 p = o and item 0 p = d)[
      set flag true
    ]
    set index index + 1
  ]
  report flag
end

to check-is-in-building
  ifelse [pcolor] of patch-here = clr-fixed-facility or any? patches in-radius 3 with[pcolor = clr-
fixed-facility][
    set in-fixed? true
  ][
    set in-fixed? false
  ]
  ifelse in-fixed? or [pcolor] of patch-here = clr-moveable-facility[
    set in-building? true
    pen-up
    if building-id-from-patch patch-here = current-destination-building
    [
      finish-memorization current-building-id current-destination-building
    ]
  ][
    set in-building? false
    if (show-crooked-paths and groupid = 1) or (show-paths and groupid = 2)[
      pen-down
```

```
    ]
    memorize-path
  ]
end

to move-avoiders-scouts
  clear-ticks
  without-interruption[
    ask workers with [name = "av-scout"][
      while [patch-here != current-destination][
        ifelse in-building?[
          let forward-position one-of patches in-radius 5 with [pcolor = clr-fixed-facility or pcolor =
clr-moveable-facility]
          ifelse building-id-from-patch forward-position = current-destination-building[
            move-to current-destination
          ][
            face-nowrap current-destination
            fd 1
            check-is-in-building
          ]
        ][
          ifelse clean-straight-path-avoider[
            set straight true
          ][
            set straight false
          ]
          avoider-scout-walk
          check-is-in-building
        ]
      ]
    ]
  ]
  reset-ticks
end

to move-agressives-scouts
  clear-ticks
  without-interruption[
    ask workers with [name = "ag-scout"][
      while [patch-here != current-destination][
        ifelse in-building?[
          let forward-position one-of patches in-radius 5 with [pcolor = clr-fixed-facility or pcolor =
clr-moveable-facility]
          ifelse building-id-from-patch forward-position = current-destination-building[
```

```
          move-to current-destination
        ][
          fd 1
          check-is-in-building
        ]
      ][
        ifelse clean-straight-path-agressive[
          set straight true
        ][
          set straight false
        ]
        agressive-scout-walk
        check-is-in-building
      ]
    ]
  ]
 ]
 reset-ticks
end

to agressive-scout-walk
  ifelse straight[
    face-nowrap current-destination
    fd 1
  ][
    ifelse seen-path = 0[
      ifelse fixed-as-destination?[
        ifelse general-clean-path[
          set straight true
          set seen-path current-destination
        ][
          set seen-path search-neighbor-in-fixed-for-agressive
          if seen-path = 0[
            set seen-path nearest-entrance-to-fixed
          ]
        ]
      ][
        ifelse clean-straight-path-agressive[
          set straight true
          set seen-path current-destination
          select-speed
        ][
          set seen-path decide-path-ahead-for-agressive
        ]
```

```
    ]
    face-nowrap seen-path
    fd 1
   ][
    ifelse distance seen-path <= 2[
     set seen-path 0
    ][
     face-nowrap seen-path
     fd 1
    ]
   ]
  ]
end

to avoider-scout-walk
 ifelse straight[
  face-nowrap current-destination
  fd 1
 ]
 [
  ifelse seen-path = 0[
   ifelse fixed-as-destination?[
    ifelse general-clean-path-avoider[
     set straight true
     set seen-path current-destination
    ][
     set seen-path decide-path-ahead-for-fixed-facility
    ]
   ][
    ifelse clean-straight-path-avoider[
     set straight true
     set seen-path current-destination
    ][
     set seen-path decide-path-ahead-for-avoider
    ]
   ]
   ifelse seen-path != 0 and seen-path != nobody[
    face-nowrap seen-path
    fd 1
   ][
    face-nowrap current-destination
    set seen-path one-of patches in-cone 5 30
    face-nowrap seen-path
    fd 1
```

```
      ]
    ][
      ifelse seen-path = nobody or distance seen-path <= 3[
        set seen-path 0
      ][
        face-nowrap seen-path
        fd 1
      ]
    ]
  ]
end

to assign-memory-to-workers
  ask workers with [name = "ag-scout"][
    let tmp item 0 memory
    set agressive-paths lput tmp agressive-paths
    ask other workers with [name != "ag-scout" and name != "av-scout" and groupid = 2][
      set memory lput tmp memory
      let index find-vertex current-building-id current-destination-building
      if index != -1[
        let route item 0 item index memory
        ifelse item 0 route = current-building-id[
          set memorized-path item 1 item index memory
        ][
          set memorized-path reverse item 1 item index memory
        ]
        set using-memory? true
        set seen-path item 0 memorized-path
      ]
    ]
  ]
  ask workers with [name = "av-scout"][
    let tmp item 0 memory
    set avoiders-paths lput tmp avoiders-paths
    ask other workers with [name != "ag-scout" and name != "av-scout" and groupid = 1][
      set memory lput tmp memory
      let index find-vertex current-building-id current-destination-building
      if index != -1[
        let route item 0 item index memory
        ifelse item 0 route = current-building-id[
          set memorized-path item 1 item index memory
        ][
          set memorized-path reverse item 1 item index memory
        ]
```

```
    set using-memory? true
    set seen-path item 0 memorized-path
   ]
  ]
 ]
end

to assign-existing-memory
 ask workers[
  if groupid = 1 and not empty? avoiders-paths[
   set memory avoiders-paths
  ]
  if groupid = 2 and not empty? agressive-paths[
   set memory agressive-paths
  ]
  if not empty? memory[
   let index find-vertex current-building-id current-destination-building
   if index != -1[
    let route item 0 item index memory
    ifelse item 0 route = current-building-id[
     set memorized-path item 1 item index memory
    ][
     set memorized-path reverse item 1 item index memory
    ]
    set using-memory? true
    set seen-path item 0 memorized-path
   ]
  ]
 ]
end
```