AMERICAN UNIVERSITY OF BEIRUT

STUDYING THE IMPACT OF UAVS ADOPTION ON THE SAFETY PERFORMANCE OF CONSTRUCTION PROJECTS USING AGENT-BASED MODELING

by
SOHEILA ZAHREDDINE ANTAR

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AN ABSTRACT OF THE THESIS OF

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Despite recent improvements and technological advancements, the construction industry is still hazardous and suffers from high rates of work-related injuries and fatalities due to unsafe site conditions and unsafe worker behavior. As such, standardized inspection procedures to monitor these unsafe conditions and acts and maintain an acceptable safety level were deemed necessary. However, traditional safety inspection practices, entailing a safety officer who navigates the jobsite, are very tedious and time-consuming. Recently, drones or unmanned aerial systems (UASs) gained some attention in the construction field and their adoption on actual construction projects for safety monitoring proved beneficial but is still scarce in the literature. As such, this research work aimed at designing an agent-based modeling tool in order to examine the impact of the adoption of drones on the safety performance of construction sites and compare it against the traditional practice. The safety performance was evaluated using three types of indicators (e.g. incident rate, safety behavior, and hazards reported) and explored for horizontal-type projects versus vertical-type projects. The effect of the dynamicity of the project, the level of site risk, and the initial attitude of workers on the proposed system was also individually studied. Experiments were conducted and results revealed that the safety performance of the project significantly improved when adopting drones as compared to the employment of a safety inspector, but the improvement is less significant under dynamic site conditions. Furthermore, better results were witnessed in the case of horizontal-type projects, high risk projects, and in projects where the initial safety culture is weak. The study contribution lies in shedding light on the potential of drones in enhancing the safety performance of projects, as well as aiding safety managers and practitioners in evaluating their safety management practices and understanding based on the project type and nature whether employing the UAS can add value to their system.

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ABBREVIATIONS

RA	risk acceptance
PR	perceived risk
RPcoeff	risk perceiving coefficient
AR	actual risk
Att	risk attitude
SI	weight on social influence
PJI	project identification
MN	management norm
WN	workgroup norm
k	total number of coworkers in the neighboring cells of the worker i
PRA^n	risk acceptance of coworker n as perceived by the worker i
AR^n_{cell}	actual risk of the cell that coworker n is working in
PMA	management risk acceptance
PR_i	perceived risk of the actual risk by worker i
h	Flight altitude
*fov*1	Vertical angle of FOV (Field of View)
*fov*2	Horizontal angle of FOV
w1	Front width of camera footprint
w2	Back width of camera footprint
l	Length of camera footprint
θ	Pitch angle
af	Front-mounted angle

v	length of the sensor of the camera
t	height of the sensor of the camera
f	focal length of the camera

CHAPTER 1

INTRODUCTION

1.1 Introduction

Although a significant improvement has been recently witnessed in the area of construction safety, the construction industry remains one of the major contributors, among other industries, to the number of work-related injuries and fatalities (Awwad et al., 2015). According to the U.S. Bureau of Labor Statistics (USBLS, 2017), the percentage of employment in the construction industry in 2017 was only 4% of the total employment in the United States while the number of fatal work injuries was around 19% of all fatal injuries in all industries (USBLS, 2017).

The reasons behind accidents on construction sites are mainly attributed to unsafe conditions and unsafe acts (Heinrich, 1959). A standardized observation system for these conditions on site is necessary in order to monitor and improve the safety performance (Laitinen et al., 1999). Safety inspection by safety officers or supervisors is a common observation practice that serves mainly for supervision and safety audits (Occupational Safety and Health Council, Hong Kong, 2005). Unfortunately, safety inspection by walking around the site is a very time consuming and tedious process, especially in large and complex building projects as well as heavy civil construction projects (highway construction, infrastructure, excavation, etc..). Safety personnel might be discouraged to regularly attend to the inspection due to its highly demanding nature in terms of both time and physical effort.

Advances in construction technology, however, have presented the industry with great potential for better control over and governance of the construction process. Specifically, the use of drones has recently been introduced into the world of construction. Drones are Unmanned Aerial Vehicles that can be managed without a pilot on board and are navigated and controlled either remotely through human intervention or autonomously. Moreover, the term UAS (Unmanned Aerial System) is sometimes used to describe the system that includes in addition to one or several unmanned aerial vehicles, the ground control station or device as well as any other needed elements like installed cameras or sensors (Irizarry et al., 2012).

The use of drones originated in military applications for distant surveillance and the realization of dangerous tasks that are too risky for human-piloted aircrafts. Today, they are being used in the public sector for transportation management, search and rescue during disasters, crime-scene photography and other cases (Irizarry et al., 2012; Howard et al., 2018). Additionally, drones are used commercially in mining, agriculture and forestry, motion picture production, and robotics (Howard et al., 2018). In construction, although the use of drones is still not very common (Howard et al., 2018), UAVs present the industry with potential means for: examining the progress of a project, job site logistics, assessing safety conditions and quality inspections, among others (Irizarry & Costa, 2016).

The application of UAVs in construction for safety monitoring is still in its prime. Only few studies have addressed this issue mainly to assess the applicability of using drones for safety monitoring and inspection. The use of an Unmanned Aerial System on an actual construction site for the purpose of safety inspection has been scarcely documented in the literature and accordingly no data regarding the efficiency of the use of such a system for improving the safety performance of a construction site has been presented. Since the collection of this type of data needs a long time with application in several projects, this study instead employs agent-based modeling to simulate the dynamics of a real construction site. The aim of this study is to understand the long- term effects of using drones for safety inspections compared to the traditional practice of safety monitoring. The two scenarios will be compared in order to assess the significance of the difference between the two cases on the improvement of the safety performance. The results will aid project managers in choosing the appropriate safety system that can provide a continuous evaluation measure for the safety conditions and acts on site for the aim of improving these conditions and minimizing the number of accidents and near misses.

1.2 Research process

A research process is conceived to set a plan of work from the beginning of this study until completion. The primary step of the research process includes a review of the available literature on safety management practices in construction and the use of drones for safety inspections as well as the theories related to the unsafe behavior of workers. Accordingly, problems and research gaps are identified which in turn form the motivation of this study and assist in developing the research objectives. Afterwards, specific research questions are set and used as a guidance for the design of the research methodology. Based on the methodology, agent-based modeling is performed followed by validation of output and simulation experiments. Finally, the results are analyzed, and discussed and conclusions and recommendations of this research are put forth.

1.3 Organization of the thesis

The organization of the thesis is summarized in Figure 1. Chapter 2 provides a research background on workers' unsafe behavior in construction, technological advances in construction safety management, and specifically the use of drones for safety in construction in addition to an overview of safety performance indicators and simulation and agent-based modeling. Chapter 3 highlights the problematic areas and gaps in the current research and accordingly presents the research objectives and questions. Chapter 4 explains the developed research methodologies as well as the employed methods. Conceptual and agent-based simulation modeling are explained in Chapter 5. Chapter 6 illustrates the techniques used for verification of the model and the validation of the output. The conducted simulation experiments are described and their results analyzed and discussed in Chapter 7. Chapter 8 concludes with the research work, limitations of the current study, recommendations for industry and future research.

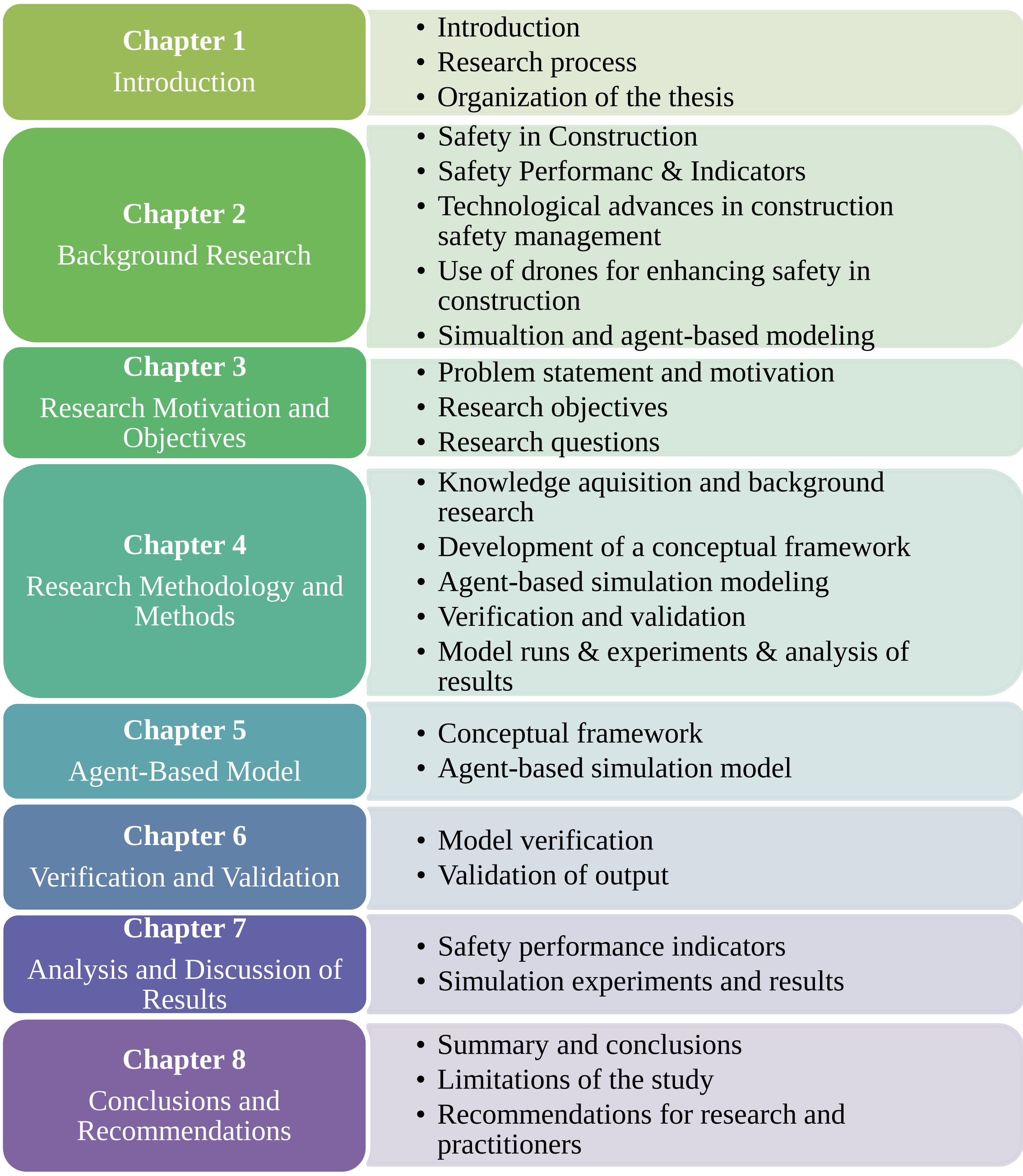

Figure 1 – Organization of the thesis

CHAPTER 2

BACKGROUND RESEARCH

A lot of studies in the literature discussed the issue of construction safety. The literature presented below covers first the main reasons for construction accidents, followed by an overview of technological advances used in construction safety management and their shortcomings. Next, the available few studies that discuss the use of drones for construction safety and monitoring are summarized. This is followed by a brief description of the kind of indicators used for measuring safety performance, and this section ends with an overview of agent-based modeling.

2.1 Safety in Construction

Many early studies related to safety on construction sites focused on finding the root causes of accidents in order to try to manage and mitigate the factors that mainly contribute to the occurrence of an accident. Abdelhamid & Everett (2000) indicated that all accidents occur due to unsafe conditions or unsafe acts. An unsafe condition is defined as “a condition in which the physical layout of the workplace or work location, the status of tools, equipment, and/or material are in violation of contemporary safety standards” (Abdelhamid & Everett, 2000). Some unsafe conditions can be totally removed, such as the case of unprotected edges. Other unsafe conditions, however, cannot be totally removed such as the presence of operating equipment. Instead, workers working in proximity of this equipment should take the necessary safety precautions. On the other hand, unsafe acts are the acts taken by workers that do not comply to safety standards. These acts can be in response to existing unsafe conditions or maybe independent from the existing conditions (Abdelhamid & Everett, 2000).

According to Guo et al. (2016), unsafe behavior can be one of three types: moving towards hazardous areas, the inappropriate use of personal protective equipment (PPEs), and incorrect operation of equipment or tools.

Laitinen et al. (1999) noted the importance of a standardized observation and monitoring method for these work conditions and workers' acts as an indicator of the safety level on a construction site. They proposed the TR-safety observation method which they used to find a safety index for the site. They found a direct correlation between the existing unsafe conditions and acts and the accident rate (Laitinen et al., 1999). These results were recently further validated in a study on small and medium construction enterprises in Turkey (Gunduz & Laitinen, 2017). Moreover, many unsafe conditions and unsafe behaviors are significantly related and thus their separation could contribute to the mitigation of accidents (Chi et al., 2013).

Environment-based safety management focuses on the elimination of unsafe conditions, while human-based safety management is directed towards reducing unsafe acts. The latter, however, is more difficult to achieve since unsafe acts by humans or workers specifically are related to their mental process and their safety attitudes which are difficult to observe, quantify, and change (Shin et al., 2014). According to Teo et al. (2005), workers exhibit unsafe behavior either due to lack of knowledge or due to poor safety attitudes. Lack of knowledge or awareness could be solved and managed through systematic training and safety campaigns especially in the area of hazard identification in order to improve the risk perception of workers (Teo at al., 2005). A study on the hazard perception of onsite personnel in Lebanon, for example, showed that workers, more than engineers and foremen, lacked the awareness towards several hazardous activities and their potential risk. This is mainly attributable to lack of training and education (Abbas et al., 2018).

In practice, practitioners resorted to punishments such as fines and penalties when workers performed violations against safety rules in order to improve workers' behavior. However, since construction is very dynamic and diverse, it is almost impossible to define standard acceptable and safe behavior for every possible situation to be encountered (Choi et al., 2016). This is why more attention is currently being placed on behavior-based safety which focuses on fostering safe behavior of workers such that they recognize and react to risk intuitively without the need for external control (Choudry, 2014; Choi et al., 2016). However, in order to change workers' unsafe behavior, the mechanism of safety behavior should be well understood, especially since the process that leads to this behavior is not solely related to internal aspects of the worker but also to other external factors.

As shown in Figure 2, the theory of planned behavior traces back behavior to behavioral intentions which are affected by factors such as the attitude of the worker as well as subjective norms (Ajzen, 1991). The safety attitude of a worker is developed through the perceived risks that this worker acquires from different types of information (Shin et al., 2014). Risk perception is defined as "the subjective judgment that people make about the characteristics and severity of a risk" (Lavino & Neumann, 2010). Subjective norms represent "a person's perceptions of significant others' expectations of his behavior" (Zhang & Fang, 2013). For the case of construction workers, significant others are mainly co-workers and management (Zhang & Fang, 2013). The final behavior implemented by the worker leads to a certain outcome that could again affect the attitude and subjective norms thus forming a feedback loop (Shin et al., 2014). Shin et al. (2014) argue that a worker sometimes may act against his intention, for example due to habit against the acquired intention. The authors suggest implementing safety measures and improvement efforts as early as possible before the workers had already acquired unsafe acting as a habit (Shin et al., 2014).

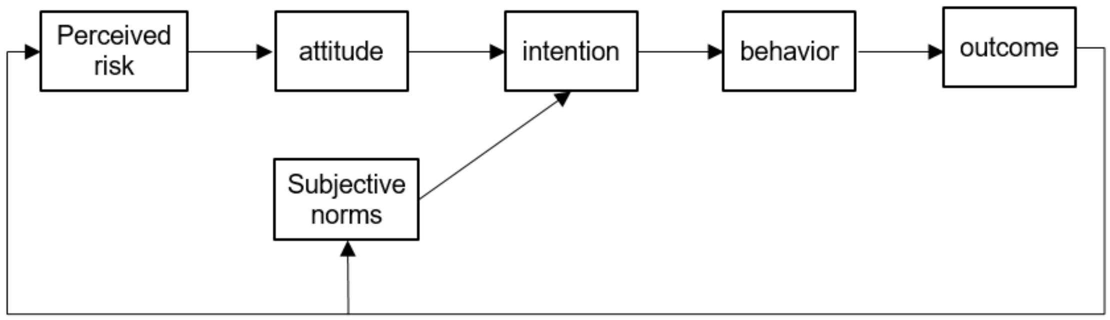

Figure 2 – Workers' mental process in relation to their safety behavior (Ajzen, 1991; Shin et al., 2014; Zhang & Fang, 2013)

Choi et al (2016) studied the "subjective norm" part of to the above mentioned theory, specifically perceived management norm and perceived workgroup norm. The study showed that perceived workgroup norms do in fact play a mediating role on the influence of perceived management norm on safety behavior. Furthermore, the results showed that a workers' social identification with the project or sense of belonging to the project strengthens the relationship between management norms and safety behavior whereas it weakens the relationship between workgroup norm and safety behavior (Choi et al., 2016).

Workers perceive a positive management norm when a standard safety management system is established where there is clear commitment to safety from all levels, safety regulations are clearly defined and imposed, safe work conditions are preserved along with providing the appropriate PPEs, workers are educated about the importance of safety, and safety personnel are employed to make frequent safety inspections to ensure that safety regulations are followed and safe working conditions are maintained and to provide the workers with the necessary feedback regarding their behavior and overall safety performance (Opfer, 1998; Helander, 1991; Jannadi, 1996; Teo et al., 2005; Zhang & Fang, 2013, Abbas et al., 2018). Furthermore, managers should be aware that the unsafe behavior of one worker might influence the behavior of other workers (Choi et al., 2016). This shows further the need for managers to have an eye on the site conditions at all times and this is where the application of drones can prove to be very useful.

2.2 Safety Performance and Indicators

Traditionally, safety performance on construction sites was measured or quantified using reactive indicators such as the Total Recordable Incident Rate (TRIR) and Lost Work Day rate (LWD) (Jazayeri, & Dadi, 2017). These indicators mainly show the magnitude of the occurrence of accidents and are reactive in the sense that they collect after the fact statistics meaning a reaction is initiated only after the incidents had already occurred. These are called lagging indicators and they are positively characterized by being “easy to collect, easily understood, comparable with each other, used in benchmarking, and useful in the identification of trends” (Lingard, 2013). However, they don’t provide any information about the reasons behind a deterioration in the safety performance and thus cannot offer any insight about the specific items that should be addressed in the system to improve this performance (Hinze et al., 2013).

The need for more proactive safety measures lead to the introduction of leading indicators for the measurement of safety performance. Leading indicators are metrics that portray the efficiency of the actions, methods and procedures taken to avoid accidents as part of the safety system (Grabowski et al., 2007). When these observations show a flaw or a weakness in the system, this means that there is a higher probability of the occurrence of an accident. Accordingly, the necessary intervention can be made in order to improve the process before any incident actually occurs. In other words, these indicators provide a method of monitoring the process during its implementation and thus giving the chance for managers to proactively respond to the collected results (Hinze et al., 2013). Hallowell et al. (2013) explained that leading indicators are similar to health-related indicators, such as blood pressure, that signal the presence of a problem or an illness that needs to be treated before the occurrence of serious complications.

Ideally, a combination of both lagging and leading indicators should be used to measure the safety performance such that leading indicators will provide measures for actions and lagging indicators will indicate whether these actions are giving effective results (SM_ICG, 2013). In the current study, safety behavior and hazards reported will be used as leading indicators (Mills et al., 2017; Nasirzadeh et al., 2018), while incident rate will be used as lagging indicator (Jazayeri, & Dadi, 2017). Details about the definitions and calculations of these indicators will be explained in later sections.

2.3 Technological Advances in Construction Safety Management

"It is believed that the availability of technology makes the construction safety reachable" (Alizadehsalehi et al., 2017). Visualization technology can improve construction safety management through facilitating the monitoring process of personnel, equipment, and the environment. To achieve this, both the location and the motion of workers and equipment can be tracked using tools that are either sensor-based (infrastructure-based) such as RFID, UWB, GPS, and WLAN, or tools that are infrastructure-free (not relying on sensors) such as cameras, IMU, and laser scanning. Usually a hybrid of both types of tools is used to achieve higher accuracy. (Guo et al., 2016; Khoury et al., 2015).

Carbonari et al. (2011) used UWB for tracking workers' positions on site in order to implement a system that alerts workers when they get close to hazardous areas in outdoor environments. The results showed good accuracy in terms of distance and the number of initiated false alarms, however, it only accounted for predefined hazardous areas and thus was not ideal for dynamic environments such as construction and needed further enhancement. Moreover, in order to identify potential hazardous areas on construction sites, Kim et al. (2016) used a real time locating system based on RFID to track the movement of workers. The path followed by these workers is then compared to the optimal route, extracted from the building information model (BIM), which is the shortest path that ideally should be taken by the laborers. According to the deviation from the optimal path and assuming that this deviation is done mainly to avoid obstacles (materials, hazards, etc.), the potential hazardous areas could be located (Kim et al., 2016). Conducted experiments showed that out of the potential hazards detected by the proposed system, 80% were in fact actual hazards. Golovina et al. (2016) proposed a method for the collection of records of incidents of proximity between workers-on-foot and heavy construction equipment, for the aim of using these records as an indicator for safety performance as well as the analysis of the situations that lead to the incidents and consequently helping in determining the root causes. The location tracking tool used for the implementation of the system was the GPS.

Although these tools and technologies are being used for tracking on-site entities, they still present several shortcomings. Infrastructure-based systems such as RFID, UWB, and GPS, which are most commonly used, require the pre-installation and calibration of a network of sensors on site. Construction environment; however, is known for its dynamic nature with frequent change of the location of equipment, materials, and personnel, and therefore repeatedly modifying the network of sensors along with these variations is highly impractical (Khoury et al., 2015). Moreover, UWB can only cover small ranges while RFID, although having a large signal cover, have a weak penetration ability through obstacles (Guo et al., 2016). On the other hand, infrastructure-free systems that mainly rely on the use of IMU require the installation of the IMU units on all the entities to be tracked and are usually combined with sensor-based systems since the use of IMU alone does not provide the needed accuracy (Khoury et al., 2015). These problems have shifted the attention of researchers towards the use of vision-based technologies relying mainly on photos and videos extracted from cameras. The advantage of this technology is that it does not rely on the use of any sensors and does not require the workers to be equipped or carrying any devices that may affect their performance or productivity. Moreover, the implementation of this technology is simple and easy and it has a low cost (Park & Brilakis, 2016; Mneymneh et al., 2018).

Park & Brilakis (2012) presented a method for the automatic detection of resources from video frames in order to initialize the tracking of these resources. The proposed method uses “background subtraction, the histogram of oriented gradients (HOG), and the HSV color histogram, one after the other, in order to narrow down the detection regions to moving objects, people, and finally construction workers, respectively" (Park & Brilakis, 2012). In order to observe and automatically detect the unsafe behavior of workers, Han & Lee (2013) proposed a framework that consists of the extraction of 3D skeletons of workers from site videos and the identification of unsafe behavior through the comparison of these 3D skeletons with motion templates and skeleton models that correspond to predefined critical unsafe acts. Mneymneh et al. (2018) utilized computer vision techniques to detect workers that are not wearing hardhats from captured videos on the construction site. Several conducted experiments yielded accurate results with high precision and recall under different conditions.

The problem with the use of computer vision techniques for detection is that these techniques might be sensitive to conditions such as lighting, dynamic environments, shadows, and occlusion which affects the accuracy of the results (Li et al., 2016). Moreover, cameras can only locate objects within line of sight and their view can be hindered by obstacles, which means it would be necessary to install several cameras in order to be able to monitor the whole site which might become expensive in large and complex projects and impractical in terms of the huge amount of data that needs to be processed (Guo et al., 2016). Drones with installed cameras can be used to overcome these problems since they can fly all around the site and change orientation which eliminates the need for more than one camera in most cases. Additionally, if the inspector or manager finds that a collected visual asset is unclear or obstructed or even if he needs additional details about a certain view, the drone can be automatically sent back to collect more information from the needed location.

2.4 Use of Drones for Enhancing Safety in Construction

UAVs can improve safety management systems by being an effective tool for monitoring the conditions on site and hence aiding in conducting safety inspections which are known for being difficult and time consuming, but crucial for maintaining the safety level on site (Irizarry et al., 2012; de Melo et al., 2017). Visual assets can be collected by the drone quickly and as frequently as necessary with the capability of transmitting the gathered data to the ground control station in real-time and thus allowing for instantaneous intervention where needed (Irizarry et al., 2012; Irizarry & Costa, 2016). Managers can get the chance to constantly visualize dangerous activities without physically being present at the location. Irizarry & Costa (2016) tested the possible applications of unmanned aerial systems for construction management issues and found that most of the collected visual assets (pictures and videos) helped in the identification of safety-related issues. However, including UAVs in the safety management system has to be accompanied with a set of standardized procedures for adequately planning the flight mission, collecting and storing the data, analyzing this data, and taking the appropriate immediate and future managerial actions accordingly (de Melo et al., 2017).

Irizarry et al. (2012) indicated that for safety inspections to be effective, they should be characterized by being frequent, having direct observations of conditions and methods, and providing direct interaction between the inspector and the workers. In addition to satisfying the first characteristic, some available drones can allow for direct observation through, first, easy navigation control by a simple user interface on the inspector’s personal smartphone or tablet, and second, the ability to issue real-time videos to this interface (Irizarry et al., 2012). Moreover, drones can be equipped with communication devices for direct interaction (Irizarry & Costa, 2016). An ideal inspection drone, according to Irizarry et al. (2012) should have the following features: "Autonomous navigation, voice interaction, environmental applicability, high-resolution cameras, multitasking application, and extended battery life".

Experiments performed with drones on the field showed that some of the safety-related issues that can be observed from the collected assets are: "damaged safety nets, missing safety guardrails, improper material storage and debris, stairs without fall protection, workers on the edge of a roof without appropriate fall protection, workers without hard-hats and personal fall arrest systems, safety platforms not installed on the entire perimeter of the building and safety platforms with uncompleted floorboard, inappropriate use of hard-hats, and safety platforms with unforeseen overload (people and scaffolding)" (Irizarry & Costa, 2016; de Melo et al., 2017). On the other hand, safety managers believe that using UAVs can mostly improve safety in the following three situations: "working in proximity of boomed vehicles/cranes, working near an unprotected edge/opening, and working in the blind spot of heavy equipment" (Gheisari & Esmaeili, 2016). Surprisingly, safety managers did not believe that UAVs can frequently aid in issues related to the adequate use of PPEs by workers (Gheisari & Esmaeili, 2016), although conducted experiments prove otherwise (de Melo et al., 2017). This indicates that construction professionals do not fully understand the potential of using UASs in improving safety on site, probably since it is still an emerging technology that has not yet been heavily applied in this area.

Kim & Irizarry (2015) indicated that the performance of UAVs can be influenced by the features of the used UAS, the project characteristics, as well as the project team features. Such features include: "Easy user interface for UAS operation, battery life of the UAS, maximum visible angle of the UAS camera, project size, duration, and complexity, team's prior experience with UAS, adequacy of training or education for UAS use as safety monitoring system, etc." The results of the study were not conclusive regarding the importance of each factor in affecting the UAV performance mainly since the number of respondents on the survey was small and since most of these respondents had no prior experience with the use of UAVs for safety monitoring and thus were unable to provide definitive answers. The authors concluded that it is currently very difficult to measure the actual performance of UASs for safety monitoring before more field tests had been conducted (Kim & Irizarry, 2015).

2.5 Simulation and agent-based modeling (ABM)

As aforementioned, the construction industry is very dynamic and evolving such that frequent changes have become a rule instead of an exception (Kim & Paulson, 2003). Moreover, construction projects include numerous participants from various organizations socially interacting with each other and the site components, making these projects perfect candidates for presentation through computer simulation, in particular agent-based modeling (ABM) rather than analytical models based on mathematical equations (Macal & North, 2009). ABM simulation is a method that uses a bottom-up approach to capture emergent phenomena of a set of agents that interact with each other and the surrounding environment (Bonabeau, 2002; Walsh & Sawhney , 2004). Agents in agent-based models are characterized by being diverse, autonomous, decision-making through a set of rules, but at the same time adaptive such that they can learn from the environment and modify their behavior accordingly (Macal & North, 2009). In agent-based models, "simple rules at the micro level create complex behavior at the macro level” which can lead to changes in the overall environment (Lu et al., 2016). All these characteristics make agent-based modeling a powerful tool that can offer a very realistic illustration of the actual system.

Agent-based models can be used to predict the output of the system, describe how the system behaves and why it behaves the way it does, experiment with if-then scenarios to understand how the system will perform under different circumstances, and suggest new questions from unexpected observations (Epstein, 2008). Moreover, these models can be used for training of practitioners, measuring the performance of the system, design and test systems that do not yet exist, and help in making decisions accordingly (Epstein, 2008; Kelton et al., 2010).

Marzouk & Ali (2013) prepared an ABM model to estimate bored piles productivity within space and safety constraints. Asgari et al. (2016) simulated the competitive construction bidding process through an agent-based model incorporating the various factors that interfere in the decision of the markup value by contractors including competition, risk attitude of contractors, and the need for work. Al Hattab & Hamzeh (2018) employed agent-based modeling to study the effect of using BIM-based design on improving the workflow taking into consideration the social interaction between participants and the dynamics of information exchange.

In the area of construction safety, the first attempt to use agent-based modeling was done by Walsh & Sawhney (2004) who tried to understand the relationship between the attitudes of owners towards production and safety and the behavior of onsite workers. The attributes used to describe workers’ behavior in the model were the production ability (productivity) and the risk-tolerance, whereas the simulated site had variable levels of danger. The results demonstrated a direct link between the safety attitude of employers and the risk-tolerance distribution in the population (Walsh & Sawhney, 2004).

The relationship between safety investment and safety performance on construction sites was investigated through an agent-based model prepared by Lu et al. (2016). Three safety investments were considered in the study: 1- the use of a novel technological tool that tracks the locations of workers and equipment and gives warning signals to workers when they are close to a hazard, 2- the use of a safety supervisor to conduct safety inspections and warn workers of close danger, and 3- promoting responsibility of coworkers' safety. The results showed that the three investments have a positive impact on the safety performance but the use of the first and third investments are favorable in terms of cost. Moreover, another important finding is that different safety investments can have different impacts on productivity and that the first investment is the most effective in reducing unsafe acts without delaying workers (Lu et al., 2016).

Choi & Lee (2017) employed agent-based simulation to model the sociocognitive process of workers' safety behaviors. This was done in order to investigate the influence of interventions such as management feedback with varying strictness and frequency on the safety behavior of workers through this process (Choi & Lee, 2017).

CHAPTER 3
RESEARCH MOTIVATION AND OBJECTIVES

3.1 Problem statement and motivation

The construction industry is known for its highly hazardous nature and high rates of work-related injuries compared to other industries. Based on the aforementioned literature, the two main reasons for construction accidents are unsafe conditions and unsafe acts. Accordingly, many studies emphasized the need for conducting regular and frequent safety inspections to monitor the conditions on site and the behavior of workers in order to control the level of safety. The most common practice of safety inspection is done by a safety officer or supervisor who navigates the site. This process, however, is very time-consuming and tedious and requires a great amount of effort especially in complex situations which are quite common on dynamic construction sites. Moreover, there are certain locations that have limited access to construction personnel and others that are very risky for the inspectors to traverse and thus would compromise their own safety. Therefore, the use of drones can help managers in overcoming the manual burden of traditional safety inspections. Drones can fly around the site collecting rapidly and frequently visual assets and can reach limited access locations. This novel technology is still in its prime and only few studies have addressed the issue of using drones for safety in construction, specifically to test the applicability of this technology for safety inspections. However, the use of drones on an actual construction site for the purpose of safety inspection has been scarcely documented in the literature and accordingly no data regarding the efficiency of the use of such a system for improving the safety performance of a construction site has been presented. Therefore, it is essential to understand the long- term effects of using drones for safety inspections compared to the traditional practice of safety monitoring. Moreover, assessing the impacts of different influencing factors such as the type and characteristics of the project is very important for optimizing the performance of the system.

3.2 Research Objectives

This study employs an agent-based simulation model to mimic the dynamics of a real construction site while taking into consideration its hazardous nature as well as the cognitive process of workers' safety behavior. As such, the overall objective of the study is to aid managers in choosing the appropriate method for rapidly inspecting and monitoring their projects so as to maintain an acceptable level of safety. The interim objectives intended from this study are as follows:

Objective 1: *Identify the difference in the resulting safety performance of the project for two cases: using a safety officer or using a UAS for safety monitoring.*

This objective will be achieved by studying and comparing three kinds of safety performance indicators: incident rate, hazards detected, and safety behavior of workers.

Objective 2: *Explore the difference in the resulting safety performance between projects with horizontal layouts and projects with vertical layouts (ex: high-rise building) when employing a UAS.*

Since the nature of vertical projects imposes certain restrictions that might hinder the performance of the UAS, this issue will be explored in order to study its effect on the resulting safety performance.

Objective 3: *Examine how varying parameters related to the characteristics of the project can influence the performance of the UAS in improving the safety performance.*

The effect of factors related to the characteristics of the project on the safety performance of the UAS will be examined including: the dynamicity of the project, the level of site risk, and the safety culture.

3.3 Research Questions

The following questions serve as a guide throughout this research for achieving the aforementioned objectives:

Q1. What difference is witnessed when employing a safety officer vs. adopting a UAS on the safety performance?

Q2. How does the type of the project (vertical vs. horizontal layout) impact the safety performance when employing a UAS?

Q3. How do different variations in the characteristics of the project influence the overall safety performance of the system?

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CHAPTER 4

RESEARCH METHODOLOGY AND METHODS

To answer the aforementioned research questions, a stepwise research methodology, summarized in Figure 3, is designed to comprise the following major tasks: 1) knowledge acquisition and background research, 2) Development of a conceptual framework, 3) Agent-based simulation modeling, 4) Verification and validation, 5) Model experiments and simulation runs, 6) Analysis of results. A brief description of each stage of the methodology is presented below:

4.1 Knowledge Acquisition and Background Research

A thorough review of studies related to using drones for safety in construction as well as the behavioral process of workers related to safety.

4.2 Development of a conceptual framework

Developing a conceptual framework that explains the process of safety inspection by a safety officer or a drone as well as the cognitive process of workers' safety behavior. The framework incorporates the interaction of these workers with the inspector, the UAV, other coworkers, and the environment (construction site). This framework in developed based on the acquired knowledge from previous studies.

4.3 Agent-based simulation modeling

Preparing a computer simulation model using Anylogic as the simulation platform. The model will include several agents with defined variables and parameters along with these agents' behavioral rules and also the rules of interactions among agents and between agents and the environment.

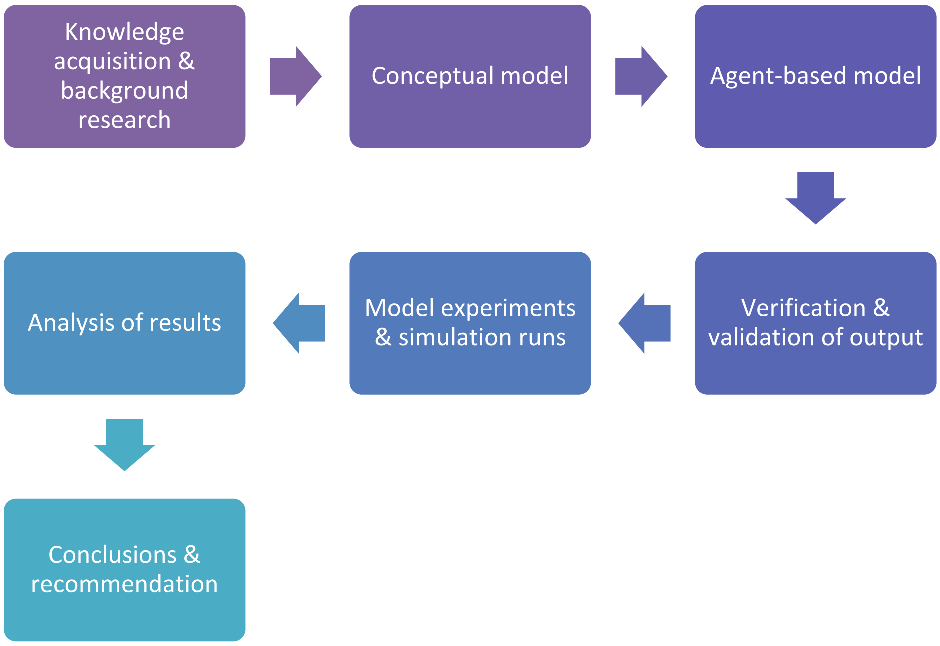


Figure 3 – Research Methodology

4.4 Verification and Validation

Verification of the model is checking whether the computerized model has been programmed and implemented correctly (Sargent, 2009). This will be done by a code walkthrough with an expert. Moreover, the mathematical equations of a simple case will be computed manually and compared with the results of the simulation. Validation of the output of the model will be done through a subjective approach based on comparing the results of the model to previous empirical findings about safety behavior of construction workers both qualitatively and quantitatively.

4.5 Model Runs and Experiments and Analysis of Results

Simulation runs will be conducted on the prepared model in order to calculate the safety performance indicators. Moreover, several scenarios will be tested by varying certain attributes related to the project so as to understand the effect of these variations on the performance. Accordingly, the results of the conducted simulation runs and experiments will be inferred and presented.

CHAPTER 5

AGENT-BASED MODEL

5.1 Conceptual framework

Unsafe behavior by workers is the main reason for construction accidents (Heinrich, 1959; Salminen & Tallberg, 1996; Hinze, 2006). Moreover, the elimination of unsafe conditions and unsafe acts by workers can effectively contribute to the prevention of accidents (Shin et al., 2014). Based on these findings, the prepared conceptual model is mainly focused around two main concepts. The first is the cognitive process of construction workers' safety behavior adopted from Choi et al. (2016), and the second is the process of safety inspection using a UAS as described and tested by de Melo et al. (2017). The effect of the interaction between these two concepts on the safety performance of the project will be studied. The conceptual framework aims at studying the difference in the safety performance between 2 proposed systems, one that employs a safety officer for safety monitoring and the other that utilizes a UAS instead. Moreover, the framework will help to depict the impact of different features of the project when using the UAS on the overall performance of the system.

The construction site is characterized by the level of risk. Site risk is most commonly defined in the literature as the product of probability and severity (Choe & Leite, 2016). Therefore, site risk is represented in the model by the probability that a worker gets exposed to an unsafe condition as well as the severity of the risk that workers will be exposed to under the unsafe condition. Moreover, as the type of the project (having a horizontal layout such as a highway construction project or a vertical layout such as a high rise building) impacts the performance of the UAV (Kim &

Irizarry, 2015; de Melo et al., 2017), this issue will also be incorporated as an attribute of the project.

Construction workers move around the site searching for work. During the execution of a task, workers can be subject to unsafe conditions and whether they commit an unsafe behavior will be determined through the depicted cognitive process in the model. This process is adopted from Choi et al. (2016). It is directly related to the risk perception and the risk attitude of workers. The actual risk on site is perceived differently between one worker to another based on the perceiving coefficient (Shin et al., 2014) which is affected by the worker's previous experience, knowledge about risk and safety, as well as his risk attitude (Mearns & Flin, 1995). However, even if two workers perceive a risk similarly, their reaction to the perceived risk is different. This reaction is a consequence of the acceptable risk by each worker which is determined by both internal factors of the worker such as attitude, as well as the interaction with external factors such as other coworkers, representing the workgroup norm, and the safety inspector or the drone, representing the management norm (Choi et al., 2016). This is due to the fact that workers are influenced by the safety behavior of their coworkers when learning the acceptable or normal behavior in a project especially in situations and types of work that they hadn't encountered previously and thus are not sure about the kind of behavior that should be undertaken. Also, workers learn the kind of behavior that is tolerated by management through the managers' or safety personnel feedback. In cases when the workers' unsafe actions are neglected, they will learn that this kind of behavior is acceptable in the project (Choi & Lee, 2017). Finally, the comparison between the perceived risk and the acceptable risk by the worker will lead to the decision of safe or unsafe behavior (Shin et al., 2014).

Regarding the management intervention, in the first case a safety inspector will wander the site to check for any non-compliance with the standard safety levels. When an unsafe condition is encountered, the officer or inspector will take the necessary measure to remedy the condition (example: if the inspector notices an unprotected opening, he will ask the concerned party to install the missing guardrails). Moreover, when the inspector notices an unsafe behavior by a worker, the worker will be informed through direct communication in order to take the appropriate action (example: if a worker is not wearing his hardhat, the inspector warns the worker about his unsafe behavior). Note that the immediate change of the worker's act from unsafe to safe for the particular instance is not conveyed in the model. Instead, the interaction will cause the worker to be more careful about the act in the future. This approach is more reasonable and realistic since the attitude of workers cannot be changed instantaneously. In other words, even if the worker wears the hardhat following the inspector's warning, this does not mean that he will wear it all the time from now on. The behavior of the worker will improve gradually based on his initial attitude. The officers' monitoring process is mainly characterized by the time required to conduct the inspection. Figure 4 summarizes the conceptual framework when a safety officer is employed for safety inspection.

For the second case, a UAS consisting of one UAV (drone) mounted with a camera and a ground control station (a tablet for example) will be used for the monitoring process and the communication between management and the workers will be done through the UAV. The assumption is that the drone will navigate the site externally without entering inside the built part of the buildings. During one complete inspection mission, the drone will inspect the site at three different levels: overview, medium view, and close-up view. Based on the study by de Melo et al. (2017), only certain percentage of requirements will be visualized at each level. Moreover, the detection of unsafe behavior and conditions from the collected photos or videos will be done through an algorithm and again only certain percentage of requirements will be detected based on the precision of the algorithm. In addition to the visualization and detection percentages, the other features of the UAV that will be considered in the model are the velocity of the drone and the battery life. Figure 5 summarizes the conceptual framework when a UAS is employed for safety inspection.

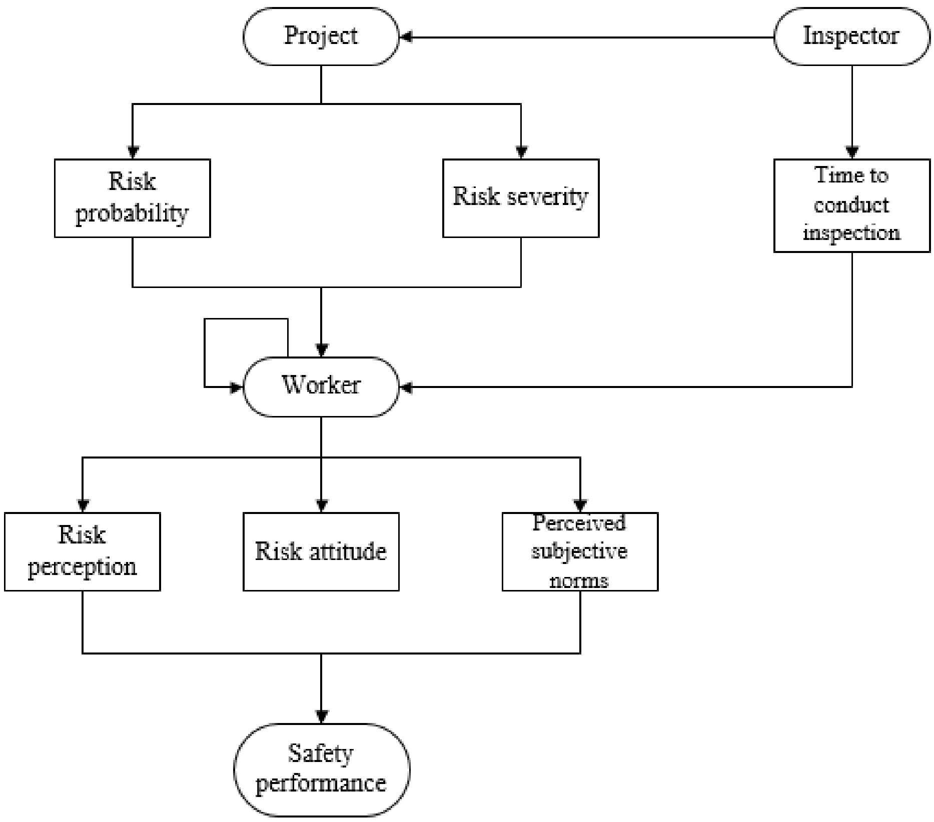


Figure 4 – Conceptual Framework: Safety Officer

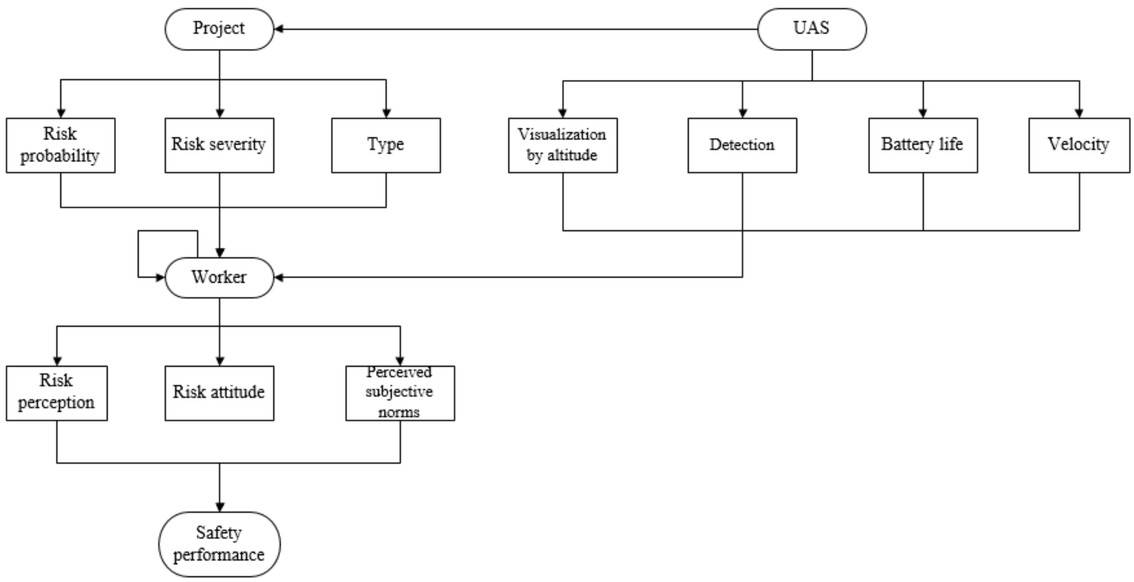


Figure 5 – Conceptual Framework: UAS

5.2 Agent-based Simulation Model

In agent-based models, agents live in a main environment where they interact with each other and the environment they live in (Bonabeau, 2002). The environment in our study is the construction project where construction activities are taking place in the concrete phase. The main agents residing and interacting in the environment are: 1- the workers, 2- the safety inspector, and 3- the drone. The safety inspector and the drone however will not coexist in the same model since the aim of the study is to compare between the two. Instead, each agent will be used in a separate model and the results of the two models will be compared.

As mentioned earlier, Anylogic will be used as a simulation platform. In Anylogic, the main environment that hosts the main agents, which is the construction project in our case, is called “Main”. This level contains populations of agents, and each population contains a certain number of single agents. The agent populations in our model are named “workers”, “inspectors”, and “drones”.

5.2.1 *Main Environment: Construction Project*

The main environment is defined by certain boundaries. It contains the agent groups, variables, parameters, events, and functions that may be related to either the main environment itself or to the agents contained in it. Moreover, the databases and charts needed to store and get the intended results are also found in the main environment. Walsh & Sawhney (2004) argued that going into excessive details of the actual geometry of the construction site and its changes with time might in fact cause ambiguities in the basic behavior of the model instead of reinforcing it. Therefore, a simple square layout is chosen to represent the construction project, having a length of 50m and a width of 50m, thus an area of $2500m^2$. Since construction sites are dynamic, different activities can be taking place in different areas, and naturally, each area is characterized by different logistics. Accordingly, the total area in the model is divided into $1m^2$ cells and each cell is characterized by certain attributes that reflect these variations. Figure 6 and Figure 7 show the 2D and 3D layout of the site from the model respectively.

These attributes are represented in the model with variables. Variables in Anylogic are used to represent characteristics of objects that are not static but change over time during one simulation run. The variables that will characterize the site are shown in Figure 8 and the relevant attributes are described below.

1- *Task availability*: either there is a task available in the cell or there is no available task since it has already been accomplished by a previous worker. At the beginning of the model, all cells contain available tasks.

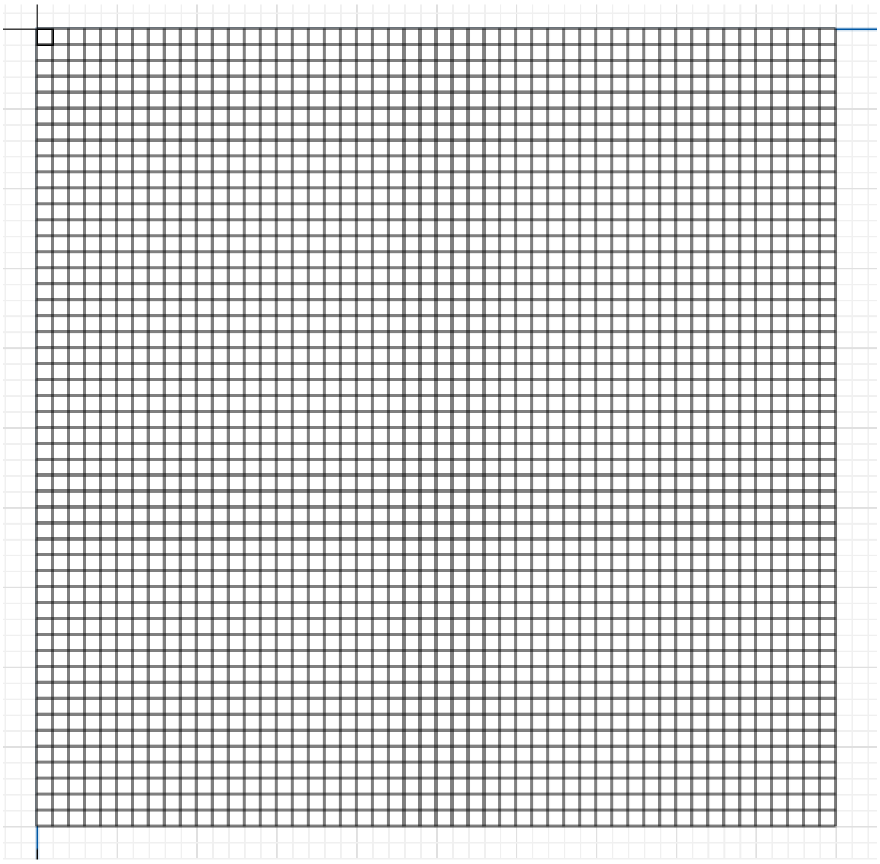


Figure 6 – "Main" environment layout-2D

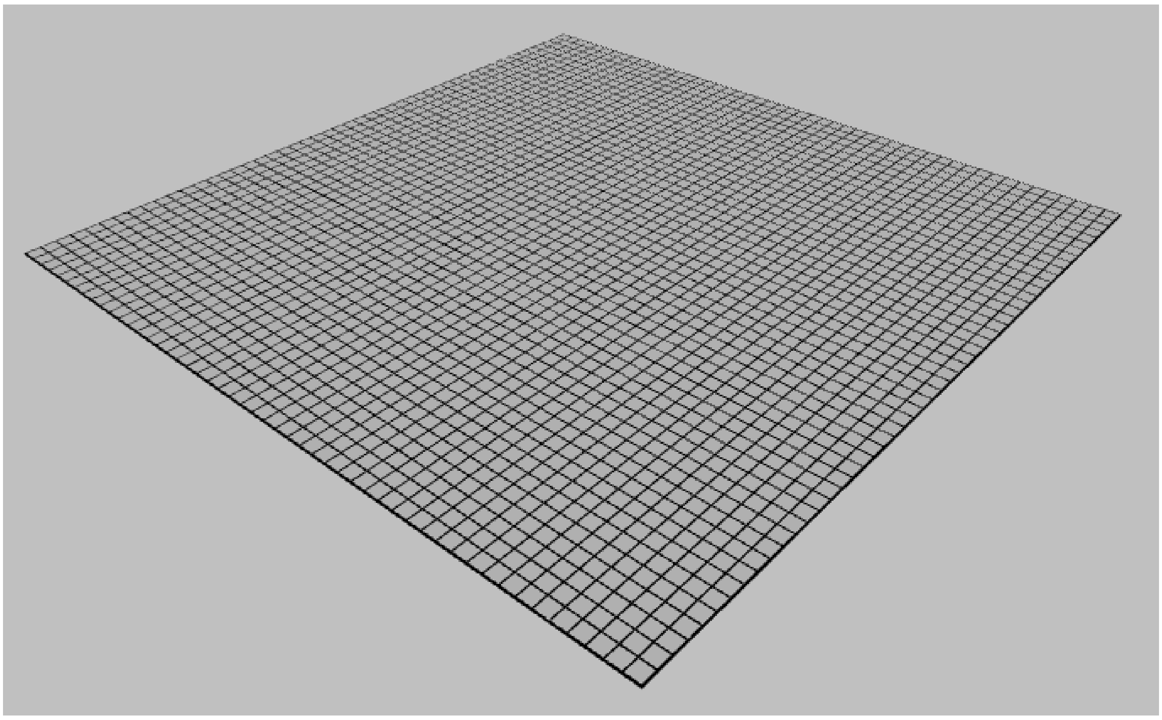


Figure 7 – "Main" environment layout-3D

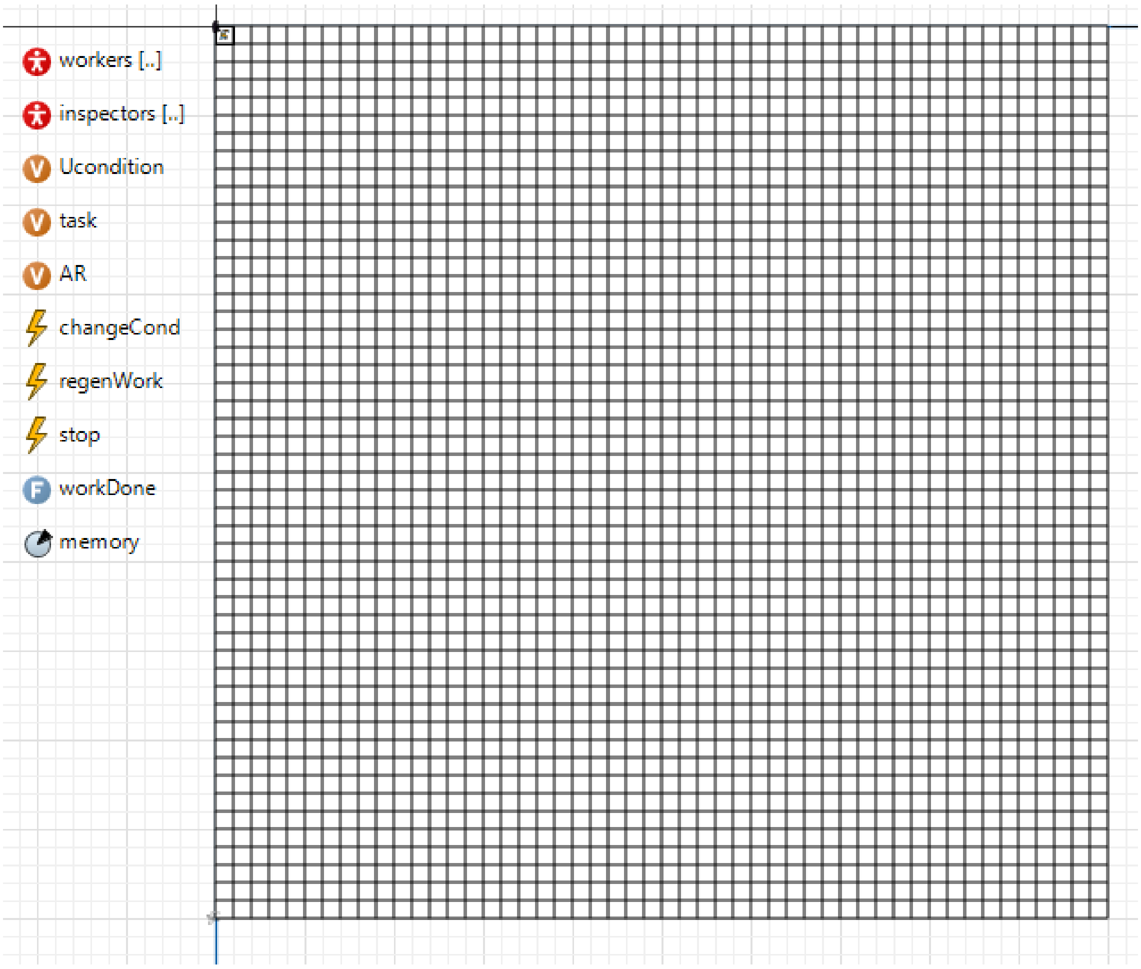


Figure 8 – Main Environment

2- Site Risk:

The level of risk on site is represented through 2 attributes: The probability of the presence of an unsafe condition as well as the average severity of the risk that the worker will be under when exposed to the unsafe condition.

a- Unsafe Condition: The probability of the existence of an unsafe condition in each cell. For instance, in the baseline model, the probability is taken to be 50%, meaning there is a 50% chance that the cell will contain an unsafe condition (modest or medium risk).

b- *Actual Risk*: the severity of the risk present in the cell or in other words, the probability of occurrence of an incident when the worker behaves unsafely.

These attributes are represented in the model through the three variables described in Table 1:

Table 1 – Summary of site variables

Attribute	Variable name	Type	Range of values	Initial value
Task availability	task	Array / integers	0: task unavailable 1: task available	1 for all cells
Unsafe condition	Ucondition	Array / Boolean	True: unsafe condition False: safe condition	Medium risk: 50% probability of being true
Actual risk	AR	Array / double	From 0 to 1	Medium risk: beta distribution (Choi & Lee, 2017)

As mentioned earlier, the values of these variables are not constant but change overtime. For example, when a worker finishes the task in a cell, the value will change from 1 to 0 to reflect that the task is no longer available in this cell. The mode of change of these variables will be described in later sections when discussing the agent groups. Three main events are present in the main environment:

1- *changeCond*: Since construction sites are dynamic and regularly changing, the site risk should change with time. This event is responsible for generating this change It is a rate-triggered event and it is set to occur twice per day. Accordingly, when this event is triggered, the variables “Ucondition” and “AR” will be revaluated for all the cells.

2- *regenWork*: This event is a “timeout”-triggered event and it is set to occur every 30 minutes. When triggered, it calls the function “workDone”. The function "workDone" is responsible for checking whether all the work has been accomplished in all cells. In other words, this function checks for the condition when the tasks in all cells become unavailable (task=0). Once this condition is satisfied, the event "regenWork" regenerates tasks in all cells (task=1 in all cells again).

3- *stop*: This event occurs once after one year in model time units to stop the simulation.

On the other hand, parameters in Anylogic are used to represent characteristics of objects that do not change over time during one simulation run. The parameter "memory" is an attribute of the worker but it is included in the "Main" environment since it has the same value for all workers. This attribute represents the time duration in which the worker is capable of remembering the perceived social norms. In other words, it is a worker's memory of their coworkers past safety-related behavior and of the management safety rules and statements. This value is assumed to be equal to 28 days in the model (Liang et al., 2018).

5.2.2 *Agent Group: Workers*

As mentioned earlier, workers are a main agent group in the model. These workers live in the main environment. The population of workers contains 50 agents. At the beginning of the simulation, workers are randomly distributed in the cells as shown in Figure 9. Since all cells initially contain available tasks, these workers will start working directly in the cell they are located in.

As explained in the conceptual model, the safety behavior of workers will follow the empirical findings of previous studies such as Choi et al. (2016) and Shin et al. (2014). These studies explain the socio-cognitive process of safety behavior. Based on

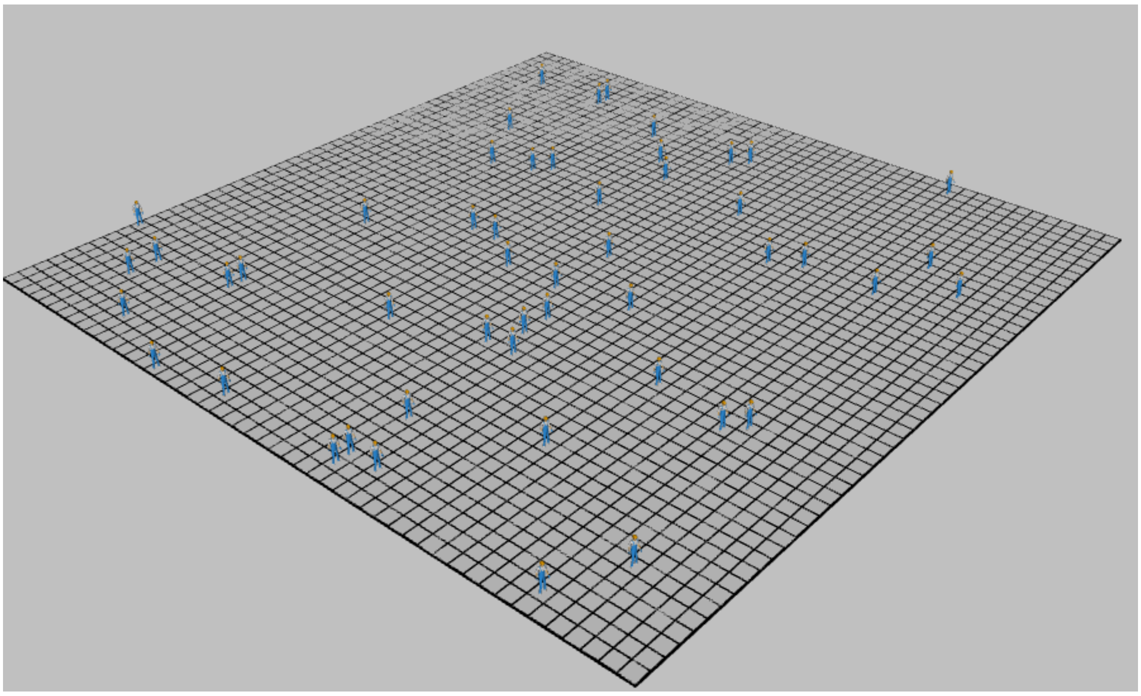


Figure 9 – Workers Distribution

the probabilities and distributions assigned for the site risk, the worker will be exposed to either a safe or an unsafe condition. When exposed to an unsafe condition, the worker will perceive a certain level of risk based on his risk perceiving coefficient. However, even if two workers perceive a risk similarly, their reaction to the perceived risk is different. This reaction is a consequence of the acceptable risk by each worker (Shin et al., 2014). Therefore, the choice of safe or unsafe behavior will be based on the below Equations 1 & 2 in the model:

$$\text{if} \quad RA < PR, \text{ the worker will behave safely,} \tag{1}$$

$$\text{but if} \quad RA > PR, \text{ the worker will behave unsafely,} \tag{2}$$

where RA = risk acceptance of the worker and PR = perceived risk by the worker.

The perceived risk is determined based on the actual risk in the cell and the risk perceiving coefficient of the worker, such that:

$$PR = RPcoeff * AR, \tag{3}$$

where RPcoeff = risk perceiving coefficient of the worker and AR = actual risk in the cell.

The risk perceiving coefficient is influenced by the worker's previous experience, knowledge about risk and safety, as well as his risk attitude (Mearns & Flin, 1995). The risk attitude shows the affinity of the worker towards taking risk. The value of risk attitude ranges from 0 to 1, 0 being the most risk-averse and 1 being the most risk-seeking. In other words, as the value of attitude increases from 0 to 1, the worker will have a higher tendency for taking risk. Therefore, when the risk attitude of the worker is close to 0 (risk-averse), then the risk perceiving coefficient will be greater than 1 since he will perceive a high value of risk and thus overestimate the actual risk (Choi et al., 2017). Moreover, the risk perceiving coefficient will change based on the change of the attitude according to Equation 4 such that the risk perceiving coefficient will increase when the attitude decreases and vice versa:

$$RPcoeff^{new} = RPcoeff^{old} - (Att^{new} - Att^{old}), \tag{4}$$

where Att = risk attitude of the worker.

As for the risk acceptance, it is determined by both internal factors of the worker such as attitude, as well as the interaction with external factors such as other coworkers, representing the workgroup norm, and the safety inspector or the drone, representing the management norm (Choi et al., 2016). Hence, the risk acceptance is calculated based on Equation 5:

$$RA = (1-SI)*Att + SI* (PJI*MN + (1-PJI)*WN), \tag{5}$$

where SI = weight on social influence, PJI = project identification, MN = management norm as perceived by the worker, and WN = workgroup norm as perceived by the worker.

The weight on social influence represents the extent to which the worker is affected by social factors (interaction with coworkers and management). This factor intensifies the effect of management and workgroup norms and attenuates the influence of the personal factor which is the attitude. Moreover, project identification represents the extent to which workers identify themselves with the project (Choi et al., 2016). Workers with stronger identification with the project they are working in will probably be less influenced by the workgroup norm and more willing to comply to management norms. Thus, this factor strengthens the effect of management norms while it weakens the effect of workgroup norms (Choi et al., 2016). Both of these findings are reflected in Equation 5.

The workgroup norm is the worker's perception of the acceptable risk of his coworkers taking into consideration the amount of info that he can retain based on his memory. In the model, the worker can only observe the coworkers that are in the 8 neighboring cells to his own. While working, the worker observes his coworkers in the neighboring cells. If the coworker is performing a safe behavior, then this worker perceives that the risk acceptance of his coworker must be less than the actual risk of the cell that the coworker is working in. On the other hand, if the coworker is performing an unsafe behavior, then this worker perceives that the risk acceptance of his coworker must be greater than the actual risk of the cell. Consequently, the worker updates his perceived workgroup norm by taking into consideration the average of the coworkers' risk acceptance as perceived by him according to Equation 6:

$$WN_i = (1\text{-}1/memory) * WN_i^{\,prev.} + 1/memory * (1/k * \textstyle\sum_0^k PRA^n), \quad (6)$$

$$\text{such that } PRA^n = \begin{cases} \text{random } (AR^n_{cell}, 1), \text{ if coworker n is performing unsafe behavior} \\ \text{or random } (0, AR^n_{cell}), \text{ if coworker n is performing safe behavior} \end{cases}$$

where memory = memory capacity, k = total number of coworkers in the neighboring cells of the worker i, and PRA^n is the risk acceptance of coworker n as perceived by the worker i, and AR^n_{cell} is the actual risk of the cell that coworker n is working in.

The management norm is the worker's perception of the acceptable risk by management in the project. If the worker is performing an unsafe behavior and he gets warned about it by the inspector, then this worker perceives that the risk acceptance of the management must be less than the perceived risk of the actual risk of the cell by the worker. On the other hand, if the worker is performing an unsafe behavior and he doesn't get warned about it by the inspector, then this worker perceives that the risk acceptance of the management must be greater than the perceived risk of the actual risk of the cell by the worker. The worker updates his perceived management norm according to the above and as reflected in Equation 7. If the worker is performing a safe behavior, the management norm will remain as it is.

$$N_i = (1\text{-}1/memory) * MN_i^{\,prev.} + 1/memory * PMA \quad (7)$$

$$\text{such that } PMA = \begin{cases} MN_i^{\,prev.}, \text{ if worker i is performing safe behavior} \\ \text{or random } (0, PR_i), \text{ if worker i is performing unsafe behavior and} \\ \text{he gets warned} \\ \text{or random } (PR_i, 1), \text{ if worker i is performing unsafe behavior and} \\ \text{he doesn't get warned} \end{cases}$$

where PMA is the management risk acceptance as perceived by the worker, and PR_i is the perceived risk of the actual risk by worker i.

For the cases when the worker is not exposed to an unsafe condition but to a safe condition instead, there will always remain a small probability that he will act unsafe if he makes a mistake during taking action, such that the mistake in this context is not related to the cognitive process but to a simple human error. If such a mistake does not occur, the worker will act safely.

Any time a worker enters a new cell or the conditions of the cell that he is working in change, all the above formulas and conditions will be re-evaluated. The attitude of the worker in Equation 5 will change if this worker undergoes a near miss or an accident. In such a case, the worker will become more risk-averse and thus the value of his attitude will decrease. Conversely, the attitude of the worker will increase to become more risk-seeking in the cases when the worker behaves unsafely but is neither warned by the inspector nor does he experience a near miss or an accident. This is because in this case the worker will underestimate the likelihood of an accident (Zhang & Fang, 2013).

5.2.2.1 Worker's State Chart and Transitions

The above explained socio-cognitive process will be reflected in AnyLogic through the behavioral states and in-between transitions in the state chart. Figure 10 shows the state chart of the workers in the simulation model.

Initially, the workers are in state "localizing" where they are randomly distributed on the cells. Note that each cell can only contain one agent. After distribution, the workers enter into the "working" state where they start accomplishing the task in the cell they are located in. The transition between the two states named "tran1" is a "timeout" transition with a negligible small duration since the workers will start working directly after localizing.

The state "working" is a composite state that contains other simple states. This is because while working, the worker can either behave safely or unsafely. Accordingly, when entering the state "working", if a certain condition is satisfied, the worker will

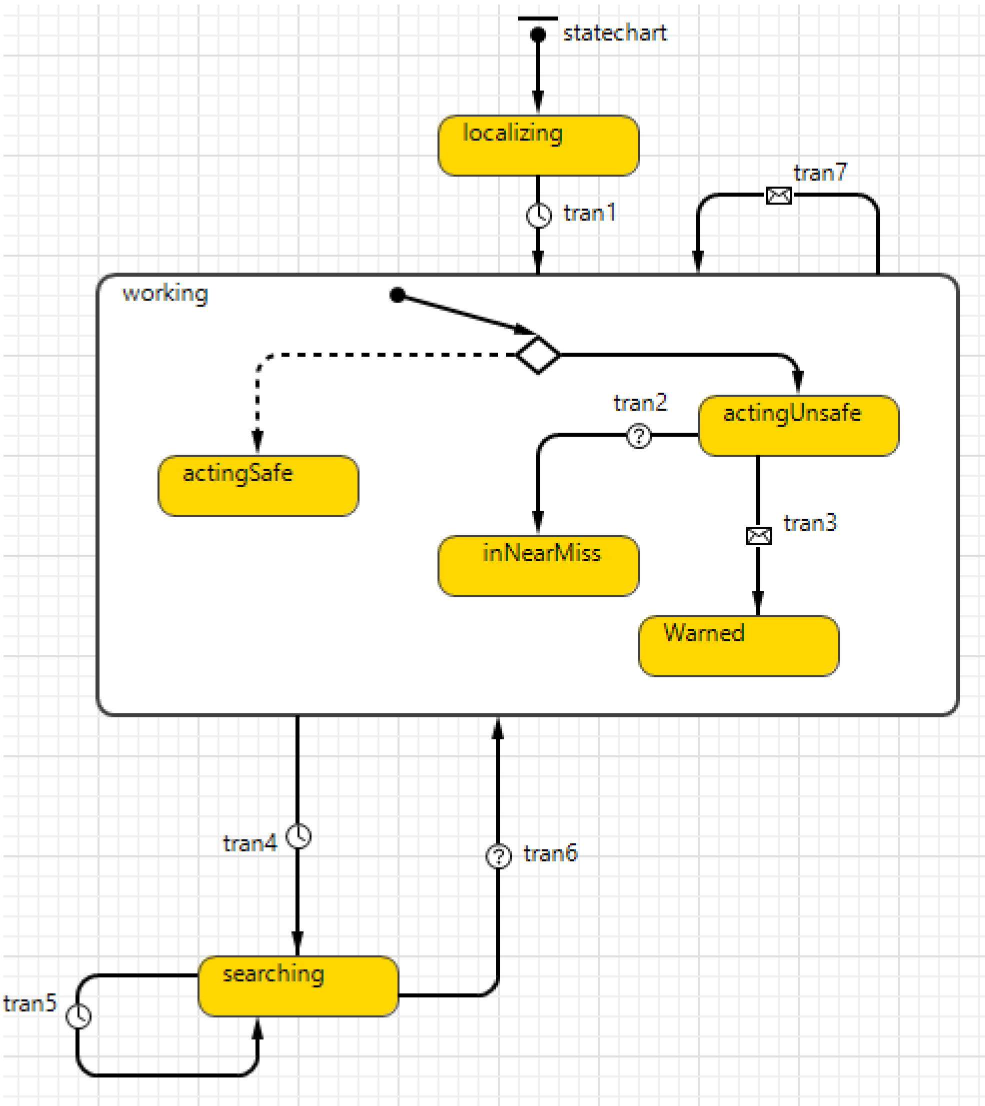


Figure 10 – Behavioral state chart of workers

move to the state "actingSafe". This condition is either when the cell has an unsafe condition and PR < RA, or if the cell has a safe condition and the worker makes a mistake. If the worker enters into the “actingUnsafe” state, there will be two possible outcomes. “Tran2” is a “condition” transition that defines the probability of the worker getting into a near miss or an accident based on the site risk. When this condition or probability is satisfied, the worker will enter to the state “inNearMiss”. On the other hand, if the worker receives a message from the inspector through the “message” transition “tran3”, the worker will move to the state “Warned”.

Transition “tran4” is a “timeout” transition that defines the duration of the task being accomplished by the worker. The duration of the task is assumed to follow a uniform distribution ranging from 4 to 16 hours. Note that the variables are assumed to follow a uniform distribution since this distribution is best suitable when there is no information clearly known regarding the actual distribution (Bruch and Atwell 2015). When this duration is finished, the worker moves to the state “searching”. When the worker enters this state, he will move to another random cell to search for an available task. This process is repeated until the worker finds a cell having the variable “task = 1” meaning that an available task that hasn’t already been accomplished by a previous worker is present. This condition is the one conveyed in the “condition” transition “tran6”. In such a case, the worker will enter back to the “working” state to start working on the new task.

Transition “tran7” is a “message” type transition. This transition is triggered by the event “changeCond” in the “Main”. Once triggered, the worker re-enters the “working” state and thus all variables and conditions will be re-evaluated based on the new cell condition and risk.

5.2.2.2 Worker's Variables & Parameters

All the factors in the socio-cognitive process explained in the previous section are represented in the "workers" agent group through either variables or parameters. Figure 11 shows the state chart of the workers with the corresponding variables, parameters, and functions. In addition to the factors explained earlier, the variables "row" and "column" represent the location of the cell in the grid that the worker is residing in. The "ActualRisk" is the actual site risk of the cell as drawn from the initial

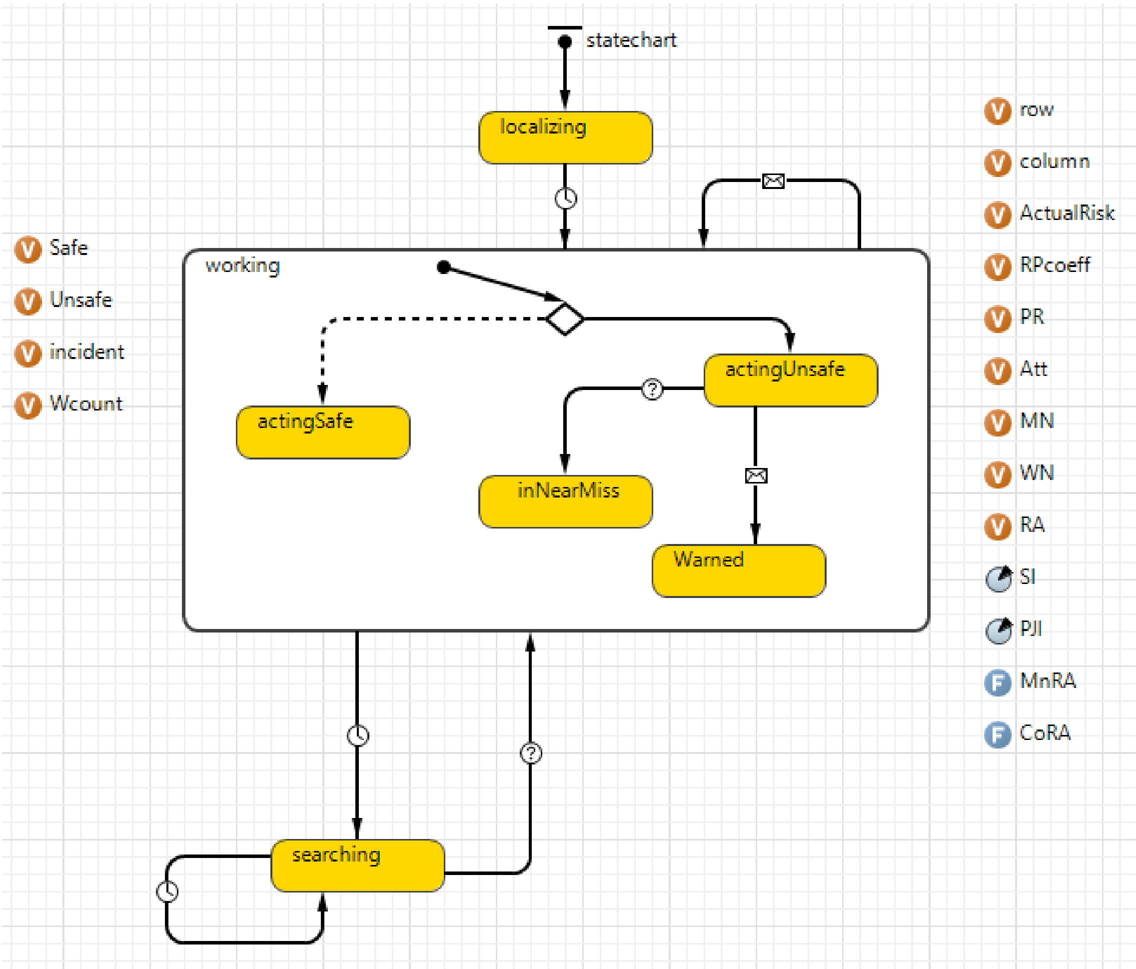


Figure 11 – Workers' variables, parameters, and functions

distribution. The variables "Safe", "Unsafe", "incident", and "Wcount" are all variables that will be used to collect statistics of the behavior of the agents in the simulation runs.

Table 2 shows a summary of the variables and parameters related to the "workers" agent along with their description and initialization. The distribution for "RPcoeff" is chosen such that the mean is less than 1 since workers usually have the tendency to undervalue the actual risk and they believe that they can control the situation (Zhang & Fang, 2013; Choi et al., 2017). As for "Att", "SI", and "PJI', the distribution is assumed to be between 0.1 and 0.9 in order to rule out extreme cases. Moreover, management norms usually tend to be stricter towards safety than workgroup norms and this is why MN is assigned values between 0.2 and 0.4 (strict) and WN is assigned values between 0.6 and 0.8 (lenient) (Andersen et al., 2015; Choi et al., 2016).

Table 2 – Workers' variables & parameters initialization

Properties	Name	Type	Initial value
Variables	ActualRisk	double	0 to 1 (medium risk-beta distribution)
	RPcoeff	double	0.4 to 1.2 uniform distribution
	PR	double	RPcoeff * ActualRisk
	Att	double	0.1 to 0.9 uniform distribution
	MN	double	0.2 to 0.4 uniform distribution
	WN	double	0.6 to 0.8 uniform distribution
	RA	double	(1-SI)*Att + SI* (PJI*MN + (1-PJI)*WN)
	row	integer	0 to 49
	column	integer	0 to 49
	Safe	integer	0
	Unsafe	integer	0
	incident	integer	0
	Wcount	integer	0
Parameters	SI	double	0.1 to 0.9 uniform distribution
	PJI	double	0.1 to 0.9 uniform distribution

Note that once the agent worker enters the state "working", it either means that the agent has entered a new cell with new properties or that the properties of the same cell have changed. Accordingly, variables "row", "column", "ActualRisk", and "PR" are all re-evaluated upon this entrance. Moreover, when the worker agent exits the state "working", the variables "Att", "RPcoeff", "WN', "MN", and "RA" are re-evaluated based on the process that occurred during working in the particular cell.

The function "MnRA" is used to calculate the management norm as perceived by the worker, and the function "CoRA" is used to calculate the workgroup norm as perceived by the worker of the coworkers in the neighboring cells to his own. In other words, "MnRA" and "CoRA" are used to calculate the second terms of Equation 6 and Equation 7 respectively. The piece of code used for the two functions is inserted below:

<u>MnRA:</u>

```
double b=0;
if (this.inState(actingSafe))//if the worker is acting safe
 b = this.MN;
if ((this.inState(actingUnsafe))||(this.inState(inNearMiss)))//if the
worker in acting unsafe and hasn't been warned
 b = uniform(this.PR, 1);
if (this.inState(Warned))//if the worker is acting unsafe and has been
warned
    b = uniform(0, this.PR);
return b;
```

<u>CoRA:</u>

```
double sum=0;
int a=0;
for( CellDirection dir : CellDirection.values() ) {
 Worker w = (Worker)( getAgentNextToMe( dir ) );
 if (w!=null){
   a++;
     if (w.inState(w.actingSafe))//if the worker next to me in a
certain direction is acting safe
   sum = sum + uniform(0, main.AR[w.row][w.column]);
     if
((w.inState(w.actingUnsafe))||(w.inState(w.inNearMiss))||(w.inState(w.
Warned)))//if the worker next to me in a certain direction is acting
unsafe
   sum = sum + uniform(main.AR[w.row][w.column], 1);}
 if (w==null){ //if there is no worker next to me in the currently
chosen direction
 a=a; //keep a as it is
 sum=sum;} //keep sum as it is
   }
if (a==0) //this means that there is no one around him at all
return this.WN;
else
return (sum/a);
```

5.2.3 *Agent Group: Inspector*

The inspector agent lives in the "Main" along with the workers. It is customary that for every 50 workers, one safety inspector should be present on site (DEVB, 1999; Cameron & Hare, 2013). Hence, one inspector agent is added in the model. The inspector roams the site moving from one cell to another to check for both unsafe behaviors by workers or unsafe conditions on the site. In order to find the average time needed for a typical safety inspection of a construction site in the concrete phase, a semi-structured interview was conducted with several safety inspectors in Lebanon. These inspectors provided the average time it takes them to inspect one level on the site along with the area of the level. Accordingly, the time it takes to inspect an area of one meter squared was calculated. This information was translated into the model through a "timeout" transition that defines the amount of time that the inspector stops in each cell. Figure 12 shows the state chart of the inspector.

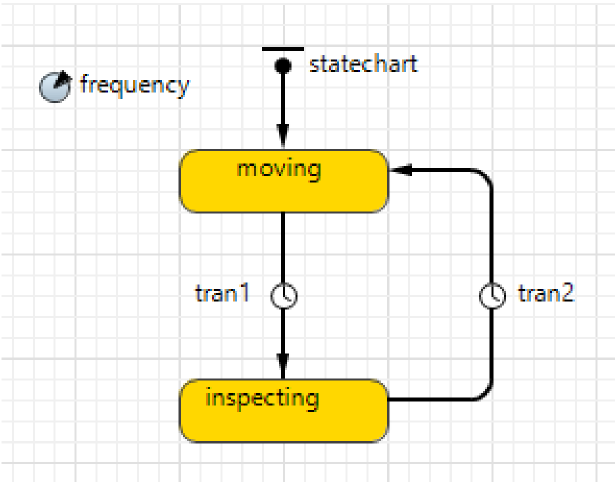


Figure 12 – Behavioral state chart of the inspector

The inspector enters into the state "moving" and starts moving from the upper most left cell downwards than upwards alternatively until reaching the upper most-right cell in order to inspect all the area. The inspector moves a distance of 1m each time to reach the next cell and then enters the state “inspecting” where he stops in the cell a certain amount of time to inspect the $1m^2$ that he is standing in and then enters back to the state “moving” to move to the next cell and so on. “Tran1” is a “timeout” transition that has a negligible duration (very small time) since the time needed by the inspector to inspect the $1m^2$ cell (obtained from the interviews) already includes the time needed to move through the site. “Tran2” is also a “timeout” transition which represents the amount of time the inspector will stay in the state “inspecting” in order to inspect a cell (having an area of $1m^2$). This time is obtained from the above mentioned interviews and it is set to a uniform distribution between 2.3 to 6 seconds.

During the inspection, if the inspector witnesses an unsafe behavior by a worker, the inspector sends a “warning” message to the worker. This message will cause the “worker” agent to move to the state “Warned”. On the other hand, if the inspector finds an unsafe condition in the cell, the “Ucondition” of the cell will change from “true” to “false” within a time assumed to be uniform between 15 to 60 minutes. This time duration was assumed because during the interviews, the inspectors indicated that they made sure that all problems are handled immediately and as fast as possible once detected.

The frequency of inspections per day is controlled through the parameter “frequency” of type “double”. The interviewed inspectors indicated that usually one inspection only is conducted per day for the whole site. Only one inspector indicated that he conducted 2 inspections per day, one in the morning and one in the afternoon. Moreover, in a study by Zhang at al. (2019), senior managers on construction sites also indicated that they usually conducted one safety inspection every day. This is why the frequency will be set to once per day in the base model.

5.2.4 *Agent Group: Drone*

The second model is the same as the first one and it contains the same agents, variables, parameters, initializations, distributions…etc., however, in this model the "inspector" agent is replaced with a "drone" agent. The behavior and details of the drone mission as used in the model are all adopted from the study done by de Melo et al. (2017) in which they tested the applicability of the use of drones for safety inspection through actual trials on two construction sites. In the study, the drone is equipped with a camera and the mission is conducted over 3 different levels: 1- Close up view, 2- Medium altitude view, and 3- Overview. The aspects and safety requirements that can and need to be visualized from each level are clearly specified before the mission. For instance, the overview is a broad view of the site that involves mainly the checking of items related to "organization and housekeeping, temporary installation, and wastes". Moreover, the medium altitude flight is focused around collective and individual protective equipment. As for the close-up view, it is mainly aimed to check items and processes such as "roof and waterproofing, concrete pouring and masonry, earthwork and foundation, equipment operation, and façade" (de Melo et al., 2017).

The heights considered in the model for each view are 10, 30, and 60 meters respectively. This means that the drone will fly over the whole site at these three different levels for each inspection.

Since only certain items are assigned to be detected at each level, a new variable is added to the "Main" in order to specify the items that can be detected at each height. The variable is named "level" and it is an array of type "String". Each cell can have one of three levels: "L" for low level, "M" for medium level, and "H" for high level. The variable is distributed through the cells such that 20% belong to the category "M", 28%

to “H”, and the remaining 52% to “L” (de Melo et al., 2017). This means that when the drone is, for instance, inspecting at the low level, it can only detect the items that are in the cells belonging to “L” as “level”.

Figure 13 shows a simplified view of the state chart of the drone. The final state chart is a copy of this one repeated for each level of flight as shown in Figure 14. However, we are going to use Figure 13 in the elaboration below for easier reference.

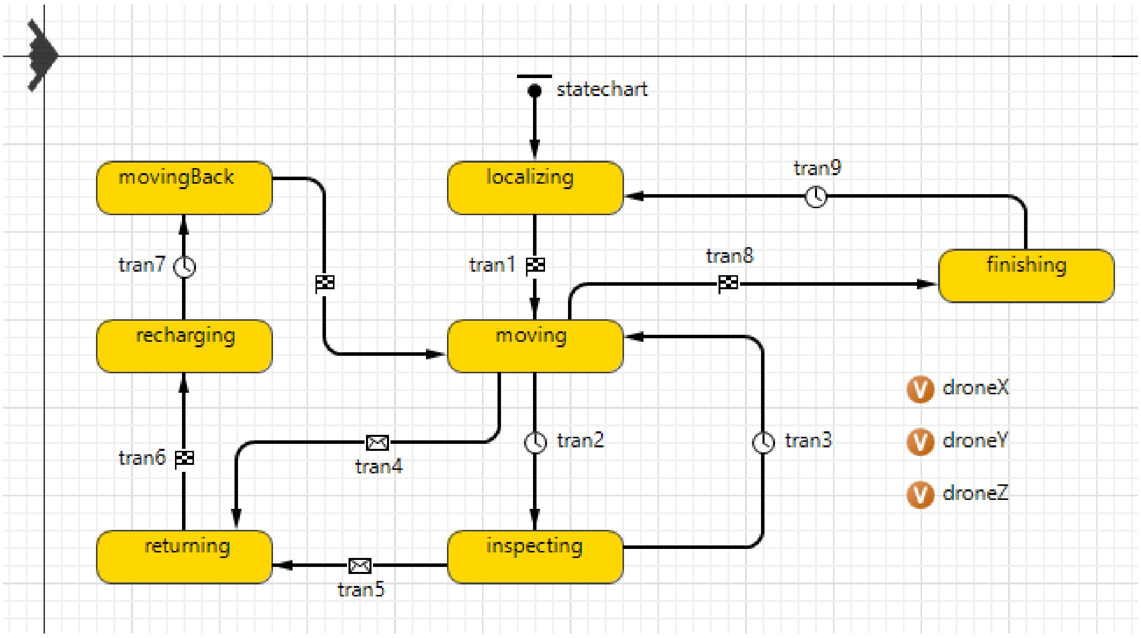


Figure 13 – Simplified behavioral state chart of the drone

The agent “drone” starts by entering the state “localizing” where the drone moves from its initial location to the point of start of the inspection mission. Upon arrival of the drone to this point it enters into the state “moving”. The transition connecting these two mentioned states is a transition that is triggered by the “agent arrival” to the specified location in the state. When the drone enters the state “moving”, it starts moving over the site along a specified path for each level of inspection. Figure 15 shows the three different paths that the drone follows on each level. These three paths are not chosen randomly; they are related to the footprint of the camera attached to the drone at each height. The details of the calculations are indicated below.

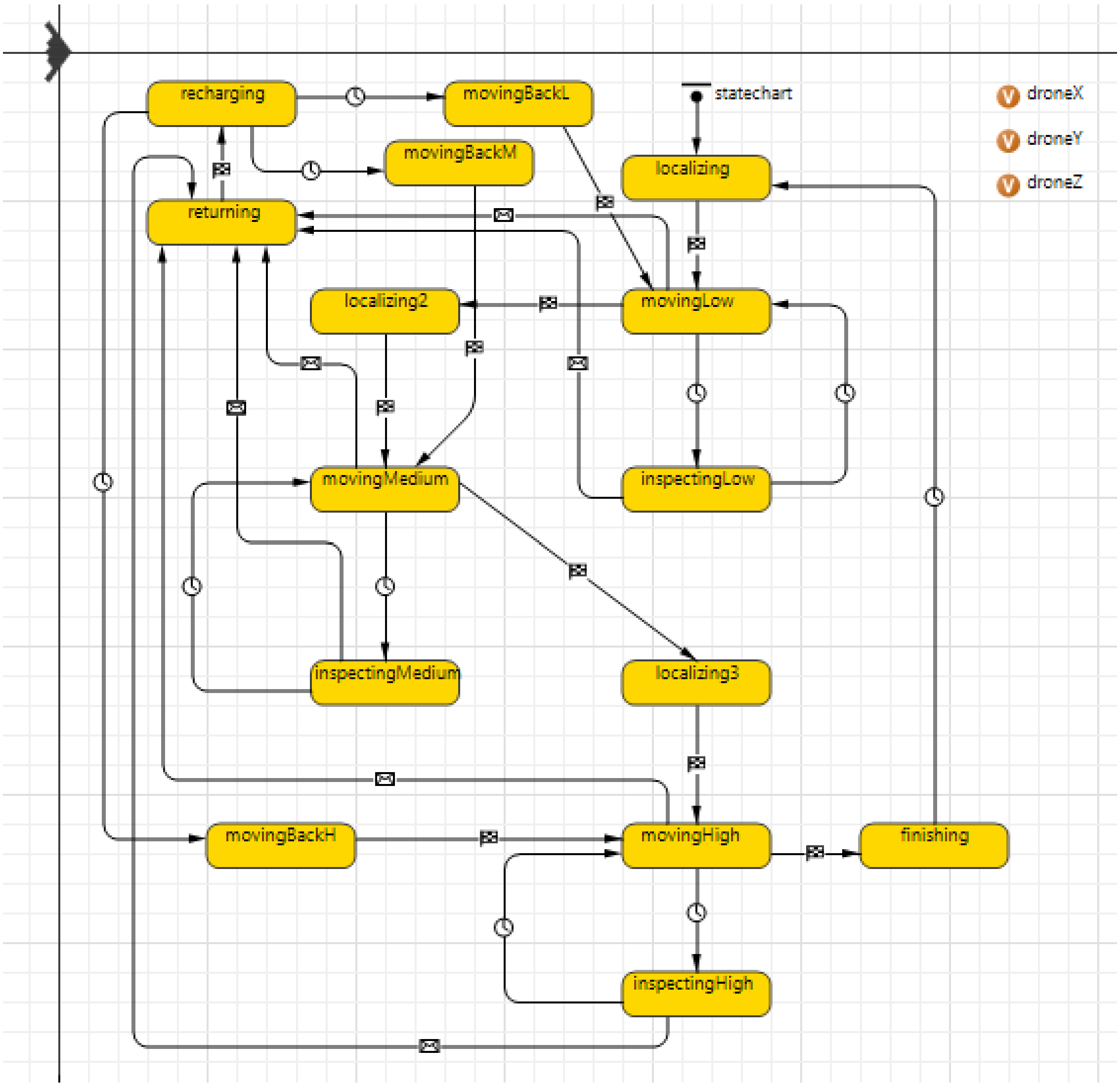


Figure 14 – Complete behavioral state chart of the drone

5.2.4.1 <u>Drone Paths</u>

In order to have an efficient inspection mission, de Melo et al. (2017) advised that the flight mission be well planned by defining the trajectory to be followed by the drone including the take-off location and the landing operation while taking into consideration all safety requirements. The path of the drone in the simulation model is

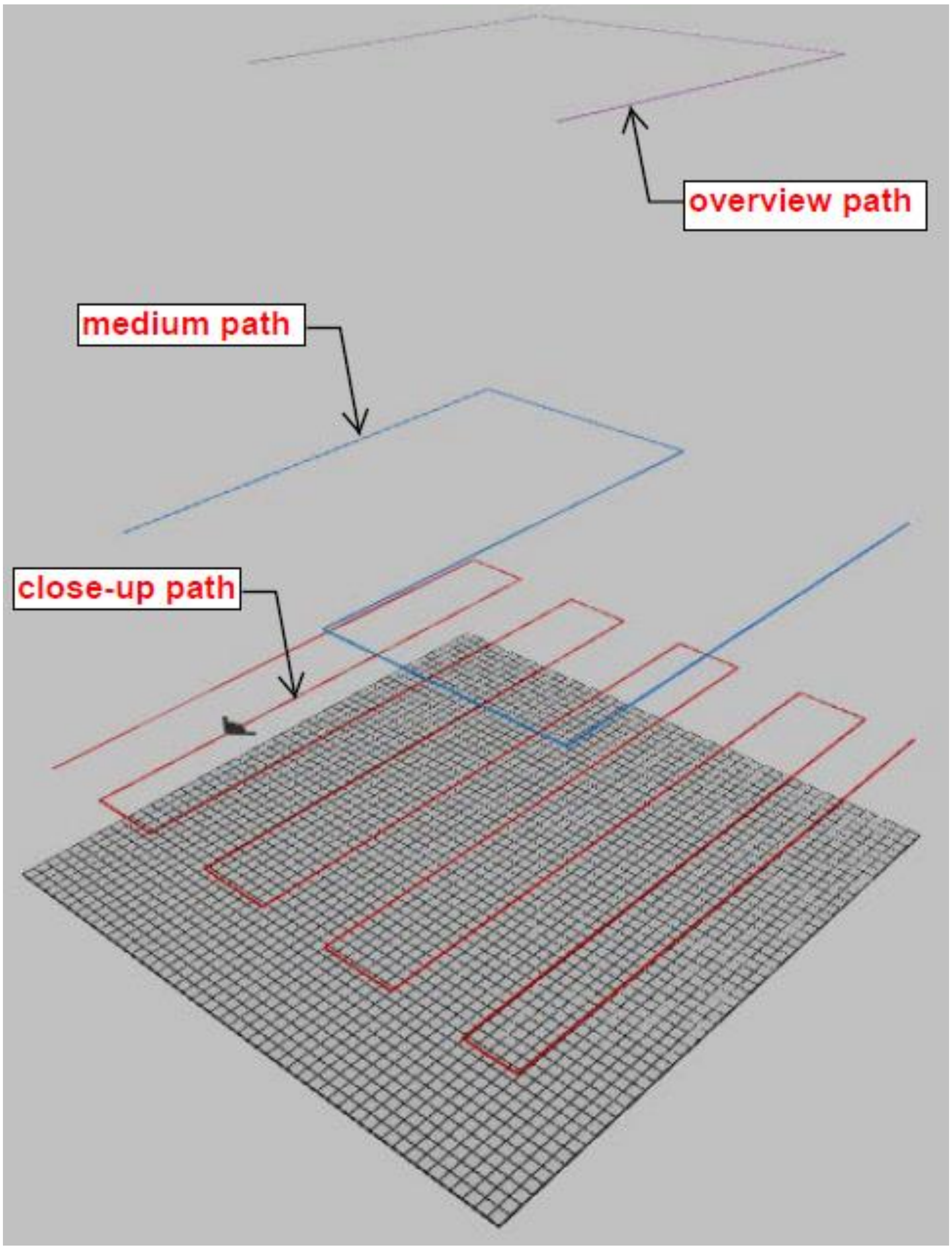


Figure 15 – Drone path

devised such that all the site area is covered by the drone flight at each level. However, since in reality the drone will have to maneuver in order to avoid obstacles and since this issue is not taken into consideration in the used paths, the assigned speed for the drone in the model is decreased by 20% in order to account for this additional time. Accordingly, the speed of the drone while flying horizontally is set to 28 mph or 12.5

m/s (35 mph minus 20%) and 10.5 mph or 4.7 m/s (14 mph minus 20%) while ascending. This speed is chosen based on the specifications of the drone used in the study by de Melo et al. (2017) which is the DJI Phantom 3 Advanced.

The calculation of the footprint of the camera depends of the characteristics of the used camera as well as the height at which the camera is operating from the ground. In order to be consistent, the type of the camera assumed to be used in the model is chosen to be the same as the one used in the study by de Melo et al. (2017). The camera used is the "Sony EXMOR camera ½0.3", 12.76 pixels of resolution, image size of 4000 _ 3000, creating pictures in JPEG and DNG format and videos in MP4".

The drone is assumed to follow a flat flying motion and the dimensions of the footprint are denoted as shown in Figure 16. The length and width of the footprint are calculated as shown in Equations 8, 9, and 10 as adopted from the study by Chen et al. (2009).

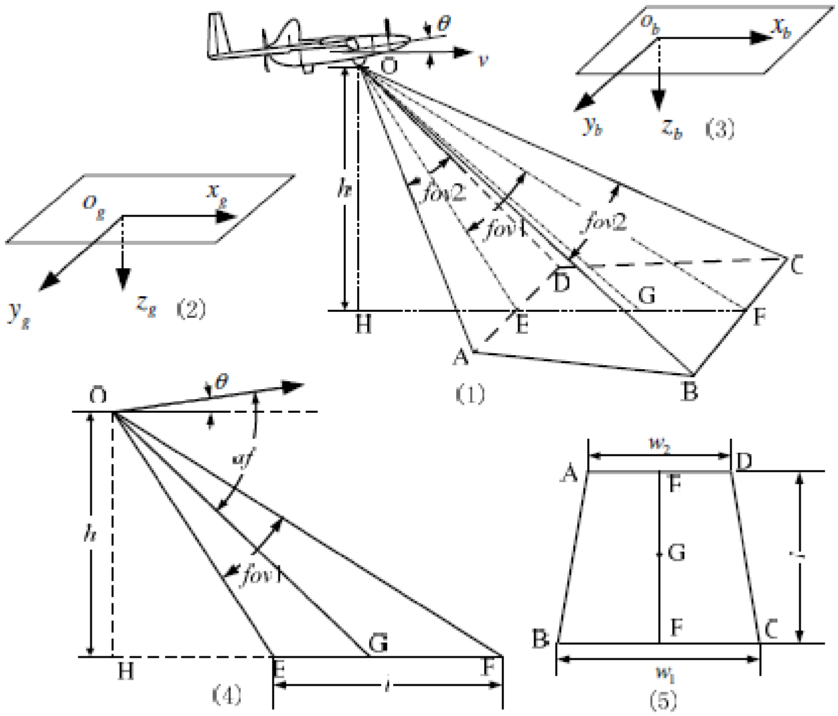


Figure 16 – The camera footprint in flat flying motion (Chen et al., 2009)

$$l = h[\cot\left(af - \theta - \frac{\mathrm{fov1}}{2}\right) - \cot(\mathrm{af} - \theta + \frac{\mathrm{fov1}}{2}) \quad (8)$$

$$w1 = \frac{2h\ tan\left(\frac{fov2}{2}\right)}{\sin\left(af - \theta - \frac{\mathrm{fov1}}{2}\right)} \quad (9)$$

$$w1 = \frac{2h\ tan\left(\frac{fov2}{2}\right)}{\sin\left(af - \theta - \frac{\mathrm{fov1}}{2}\right)} \quad (10)$$

where

h - Flight altitude.

*fov*1 - Vertical angle of FOV (Field of View).

*fov*2 - Horizontal angle of FOV.

w1 - Front width of camera footprint.

w2 - Back width of camera footprint.

l - Length of camera footprint.

θ - Pitch angle, $\theta \in (0,\frac{\pi}{2})$

af - Front-mounted angle which is the included angle between longitudinal axis of UAV and bisector of *fov*1.

fov1 and fov2 are related to the performance of the camera, and they are calculated as per Equation 11 and Equation12 respectively.

$$fov1 = 2\,\mathrm{arctan}(\frac{v}{2f}) \quad (11)$$

$$fov2 = 2\,\mathrm{arctan}(\frac{t}{2f}) \quad (12)$$

where

v – length of the sensor of the camera

t – height of the sensor of the camera *f* – focal length of the camera

For the chosen camera, *v* = 6.2 mm, *h* = 4.65 mm, and *f* ranges from 4.3 to 513 mm and assumed to be 10 mm in the calculation.

Accordingly,

$$fov1 = 2\arctan\left(\frac{6.2}{2*10}\right) = 34.44\ degrees$$

$$fov2 = 2\arctan\left(\frac{4.65}{2*10}\right) = 26.17\ degrees$$

Which means that for the close up view where *h* = 10m:

It is assumed that the camera lens is directed downwards, so *af* = 90 degrees.

$$l = 10\ [\cot\left(90 - 0 - \frac{34.44}{2}\right) - \cot\left(90 - 0 + \frac{34.44}{2}\right) = 4.65\text{m}$$

$$w1 = \frac{2*10\ tan\left(\frac{26.17}{2}\right)}{\sin\left(90 - 0 - \frac{34.44}{2}\right)} = 6.36m$$

$$w2 = \frac{2*10\ tan\left(\frac{26.17}{2}\right)}{\sin\left(90 - 0 + \frac{34.44}{2}\right)} = 6.36m$$

Therefore, the area that will be detected by the drone at this level is approximately a 6 by 5 square as shown in Figure 17. The drone moves a distance of 5m each time to reach the next inspection area and then enters the state “inspecting” where it stops at the center of the area for 5 seconds to capture the needed photos and videos in all directions, then enters back to the state “moving” to move to the next area and so on.

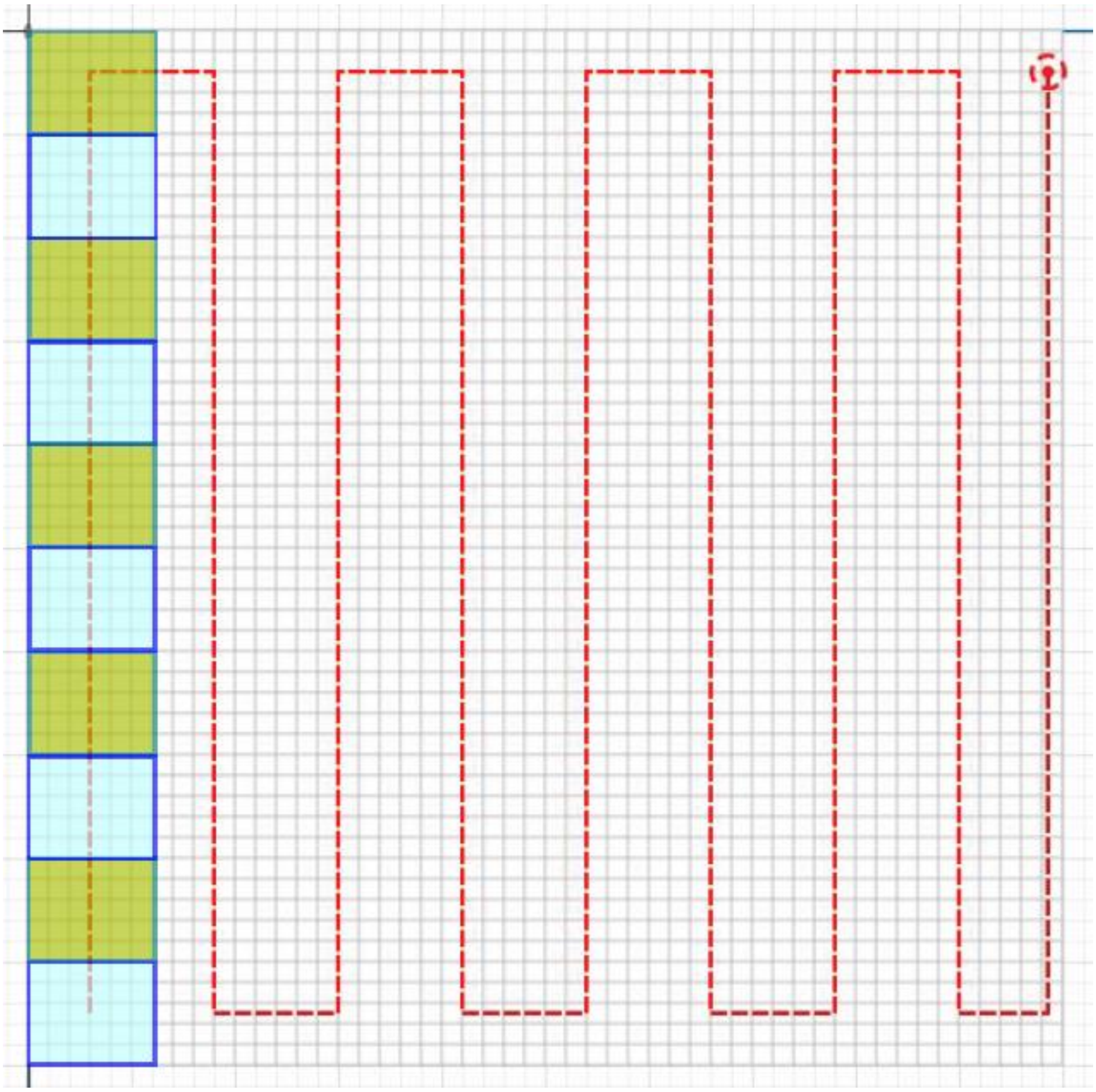


Figure 17 – Area detected by the drone at the close-up view

Similarly, for the <u>medium view where *h* = 30m</u>:

$$l = 30\ [\cot\left(90 - 0 - \frac{34.44}{2}\right) - \cot\left(90 - 0 + \frac{34.44}{2}\right) = 13.95\text{m}$$

$$w1 = \frac{2 * 30\ tan\left(\frac{26.17}{2}\right)}{\sin\left(90 - 0 - \frac{34.44}{2}\right)} = 19.09m$$

$$w2 = \frac{2 * 30\ tan\left(\frac{26.17}{2}\right)}{\sin\left(90 - 0 + \frac{34.44}{2}\right)} = 19.09m$$

Therefore, the area that will be detected by the drone at this level is approximately a 20 by 14 square as shown in Figure 18. The drone moves a distance of 14m each time to reach the next inspection area and then enters the state “inspecting” where it stops at the center of the area for 5 seconds to capture the needed photos and videos in all directions, then enters back to the state “moving” to move to the next area and so on.

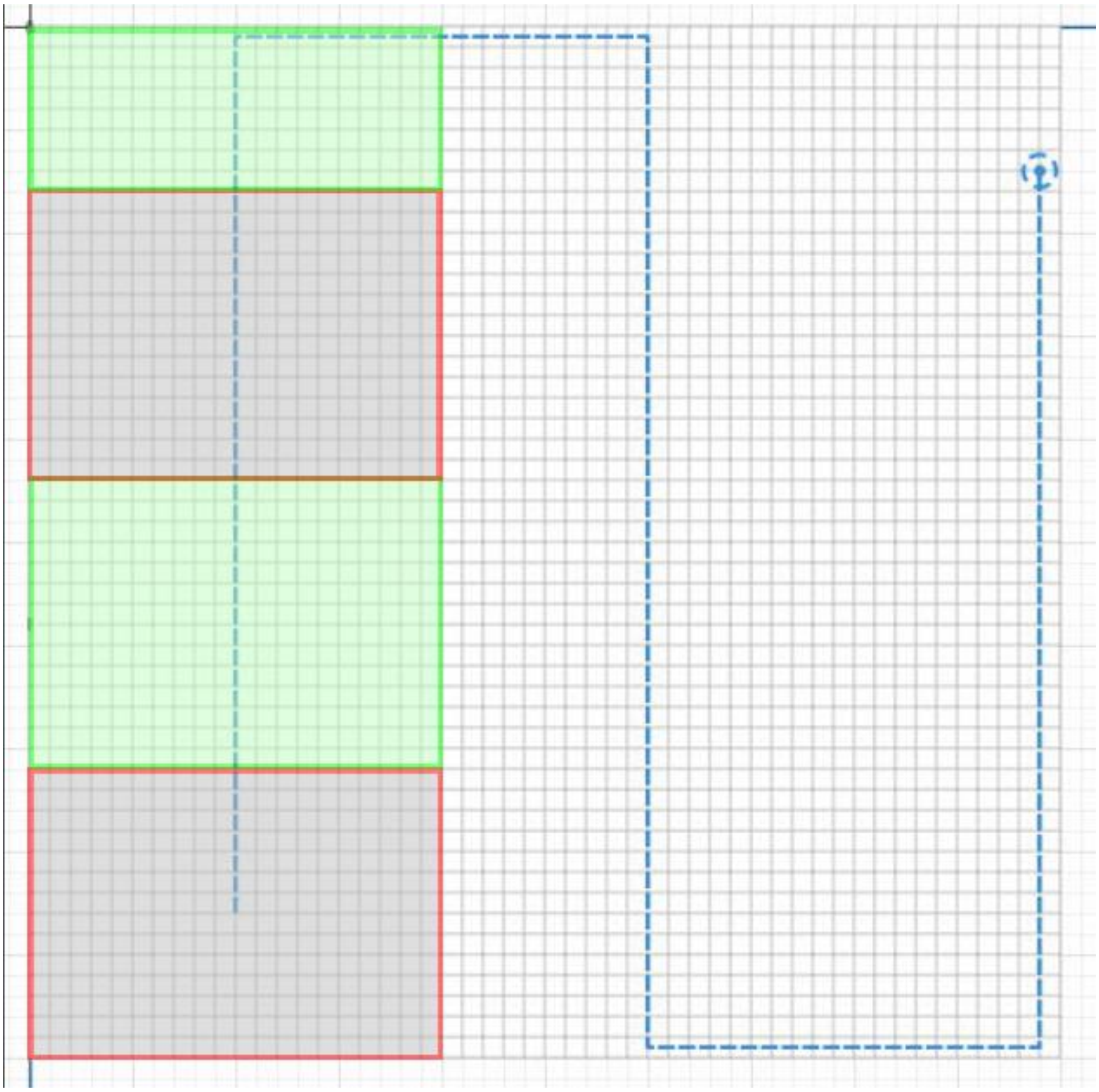


Figure 18 – Area detected by the drone at the medium altitude view

For the overview where h = 60m:

$$l = 60\ [\cot\left(90 - 0 - \frac{34.44}{2}\right) - \cot\left(90 - 0 + \frac{34.44}{2}\right) = 27.9\text{m}$$

$$w1 = \frac{2 * 60\ tan\left(\frac{26.17}{2}\right)}{\sin\left(90 - 0 - \frac{34.44}{2}\right)} = 19.09m$$

$$w2 = \frac{2 * 60\ tan\left(\frac{26.17}{2}\right)}{\sin\left(90 - 0 + \frac{34.44}{2}\right)} = 38.19m$$

Therefore, the area that will be detected by the drone at this level is approximately a 38 by 28 square as shown in Figure 19. The drone moves a distance of 28m each time to reach the next inspection area and then enters the state "inspecting" where it stops at the center of the area for 5 seconds to capture the needed photos and videos in all directions, then enters back to the state "moving" to move to the next area and so on.

At the inspection area and in the state "inspecting", the photos that are taken by the camera are scanned for detection through a certain algorithm. The mechanism for detection along with its performance are adopted from the study by Mneymneh et al. (2018). Mneymneh et al. (2018) devised a computer vision technique capable of detecting unsafe behavior of workers such as not wearing hardhats from captured videos on the construction site. The time needed for the detection of the unsafe acts/conditions by the algorithm is approximated for each area based on the findings of this study. For the close up view, it is approximated to be 5 seconds, for the medium view 50 seconds, and for the overview 180 seconds.

Figure 20 shows the percentage of safety inspection requirements visualized at each level for project A (horizontal-type) and project B (vertical-type). According to the

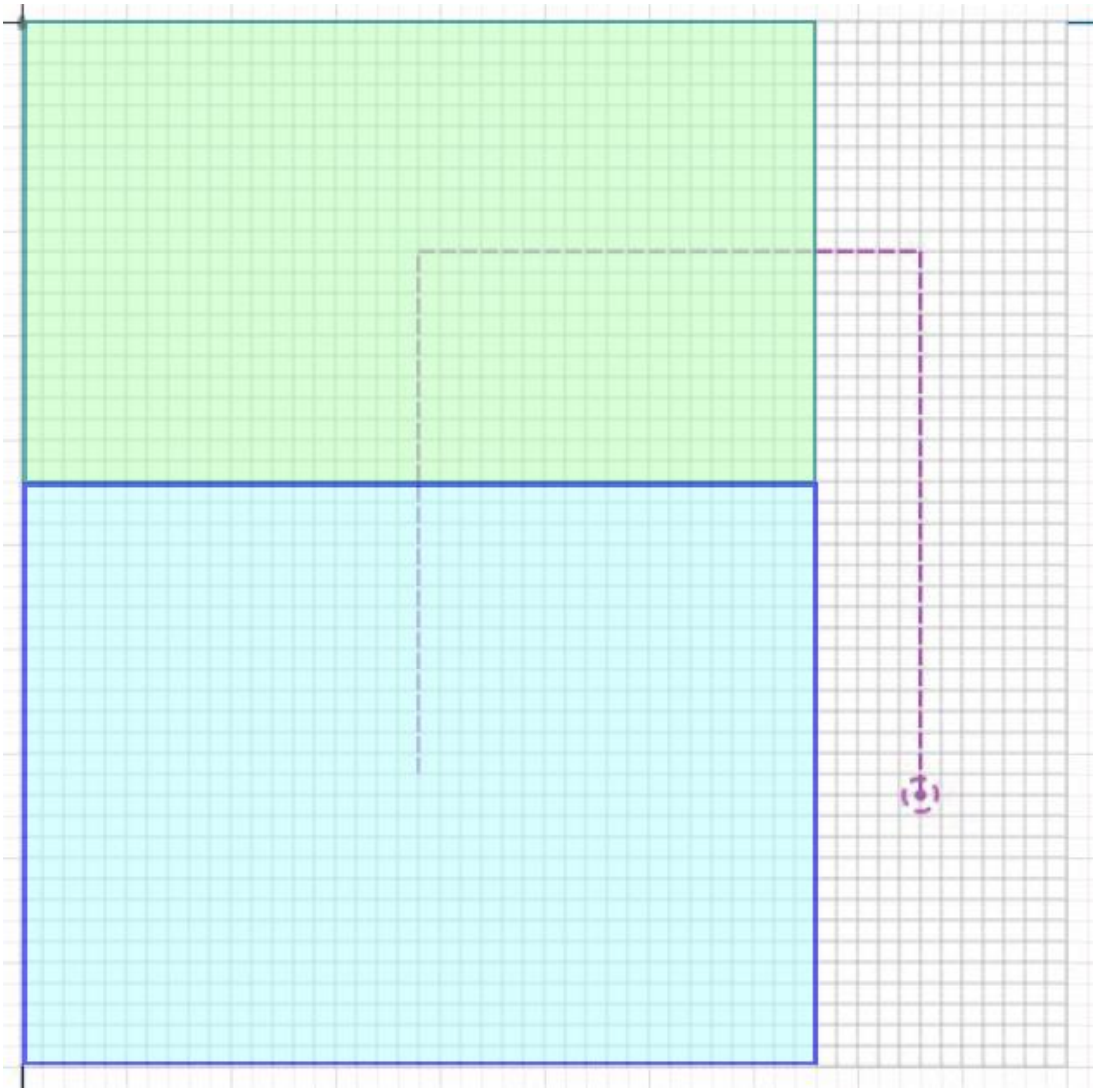


Figure 19 – Area detected by the drone at the overview

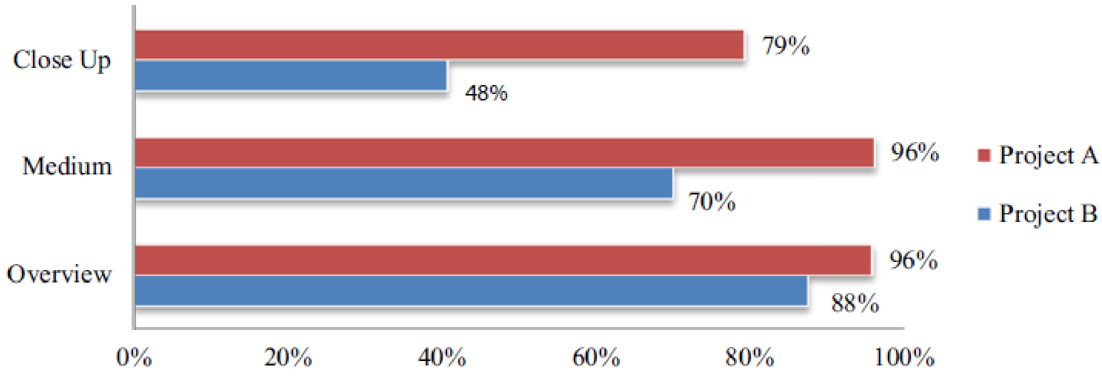


Figure 20 – Percentage of safety inspection requirements visualized by snapshots (de Melo et al., 2017)

tests done by de Melo at al. (2017), for horizontal-type projects, 79% of the items at the close-up view will be visualized. As for vertical-type projects, 48% of the items at the close-up view will be visualized. Moreover, the algorithm used by Mneymneh et al. (2018) is capable of detecting 86% of the instances in outdoor near range visual assets. These findings are incorporated in the inspection process in the state “inspecting”. The code for this is indicated below:

```
{int c = ((int)( getX() / main.spaceCellWidth() ))-3;
int r = ((int)( getY() / main.spaceCellHeight() ))+2;
if (direction != 0){
for (int i=r; i>r-5; i--){
    for (int j=c; j<c+6; j++){
      if (main.level[i][j]=="L"){
         if ((main.getAgentAtCell( i, j )!=null) &&
(((Worker)main.getAgentAtCell( i, j )).inState(Worker.actingUnsafe)))
            { if( randomTrue( 0.79*0.86 ) )
               main.getAgentAtCell( i, j ).receive( "warning" );}

         if (main.Ucondition[i][j]==true){
              if( randomTrue( 0.79*0.86)){
                Fixer fx = randomWhere (inspSpace.fixers, f ->
f.inState(Fixer.waiting));
                fx.destinationX = j* main.spaceCellHeight();
                fx.destinationY = i* main.spaceCellWidth();
                send ("fix", fx);
                   }}}}}}}
```

For both the medium view and the overview, 96% of the items will be visualized in horizontal-type projects (de Melo at al., 2017). For vertical-type projects, 70% of the items will be visualized at medium view and 88% at overview. Moreover, 84% of the instances in all the above cases will be detected in outdoor far range visual assets (Mneymneh et al., 2018). Note that for the overview inspection, only unsafe conditions will be visualized since the behavior of workers is very difficult to detect at such an elevated altitude.

Similar to the case of the inspector, during the inspection by the drone, when an unsafe behavior by a worker is detected, a “warning” message will be sent to the worker. Moreover, if an unsafe condition is detected, the “Ucondition” of the cell will change from “true” to “false” within a time assumed to be uniform between 15 to 60 minutes.

Since the battery of the drone has a certain lifespan, the drone will need to return for charging or replacement of the battery when the battery is close to becoming empty. Manufacturers usually advise that the drone returns when the battery charging level reaches 30% (Costa et al., 2016). Accordingly, when the lifespan of the battery is down to 30% (whether during “moving” or “inspecting”), the drone agent will enter to the state “returning” where it will return to its initial location through a straight path which is the shortest path between its current location and the location it started the mission from on the ground. Both “tran4” and “tran5” are message transitions responsible for transitioning the drone to the state “returning” once a message is received that the battery has reached 30%.

Next, when the drone reaches the initial location, it enters to the state “recharging”. The UAV assumed to be used in the model is the DJI Phantom 3 Advanced (de Melo at al., 2017). The battery of this drone needs around 1.5 hours for recharging. However, more than one battery can easily be obtained on site in order to avoid waiting for recharging. Therefore, “tran7” which is a “timeout” transition is set to 5 minutes which is assumed to be the time needed to replace the battery of the drone. When these 5 minutes pass, this transition is triggered and the drone enters into the state “movingBack” where it returns to the exact location that the inspection was interrupted at and then continues the mission by entering again to the state “moving”. Finally, when the drone reaches the end of the highest path assigned in the mission (when “tran8” which is an “on arrival” transition is triggered), it will enter into the state “finishing” where it will return back to its initial location through a straight path.

This inspection by the drone can easily be repeated as much as needed per day since no physical effort will be needed and since the safety of any personnel is not compromised. The “timeout” transition “tran9” represents the time between inspections. This time is set to 10 minutes in order to take into consideration the time needed to replace the battery. According to the above, if the flight mission needs around 45 minutes to be completed including the time needed by the algorithm for detection, then in an 8 hours working day, around 8 inspections can be conducted per day.

CHAPTER 6
VERIFICATION AND VALIDATION

An important part of the process of developing an agent-based model is the verification and validation of the model in order to ensure the credibility of the model for its intended use. Verification is making sure that the computerized model has been programmed and implemented correctly to do what it is meant to do as per the conceptual model and that it does not contain any programming errors that may distort the results. This step is usually done along with the process of model building and after finalizing the model but before validating it and conducting the needed experiments (Grabner, 2018). Model validation, on the other hand, is defined as “the process of determining whether a simulation model is an accurate representation of the system, for the particular objectives of the study” (Law, 2008).

6.1 Model Verification

The methods used for verification of the model are adopted from Sargent (2013). First, during the process of building the model, animation was used to check the model’s operational validity in order to make sure that agents appeared to behave graphically as intended in the code (Sargent, 2013). In case of inconsistency, the code was reviewed and corrected where needed. Moreover, input-output relationships were checked by computing all mathematical equations manually for specific input values and the results compared with those of the simulation (Ormerod & Rosewell, 2006). In order to verify the final developed model, a structured walkthrough was conducted with an expert to make sure there are no errors in the model. This was done by reviewing and explaining the code line by line to the expert to check its correctness (Sargent, 2013).

6.2 Validation of output

Several techniques exist to validate agent-based models. The appropriate validation method shall be chosen based on the accessible data and the goal or purpose of the model. For our case, since little data is available from the actual system (non-observable system), a subjective approach based on exploring the model behavior as described by Sargent (2013) is chosen. This method is centered around exploring the output behavior of the model. This can be done by comparing the results of the baseline model to empirical findings about safety behavior of construction workers from previous studies. This type of validity is distinguished by Gon et al. (2000) as the replicative validity (i.e., "the model matches data already acquired from the real world"). The output of the model can be explored qualitatively such that the general trend in the output is checked for compliance with previous findings, or quantitatively such that both the trend and the magnitude of the output are investigated (Sargent, 2013).

First, the qualitative conformity of the replicative validity was tested. The perceived strictness of the management norm represented by the risk acceptance by management, the perceived strictness of workgroup norm represented by the risk acceptance of workers as a group, and the individual risk acceptance are compared. Accordingly, Figure 21 shows the change in the mean of the risk acceptance of each of the three aforementioned entities with respect to time in the baseline model. The results show that management norm is stricter than workgroup norm since the risk acceptance of the latter is greater and that the risk acceptance of the individual worker stands between that of management and workgroup. These results replicate the empirical findings by Choi et al. (2016).

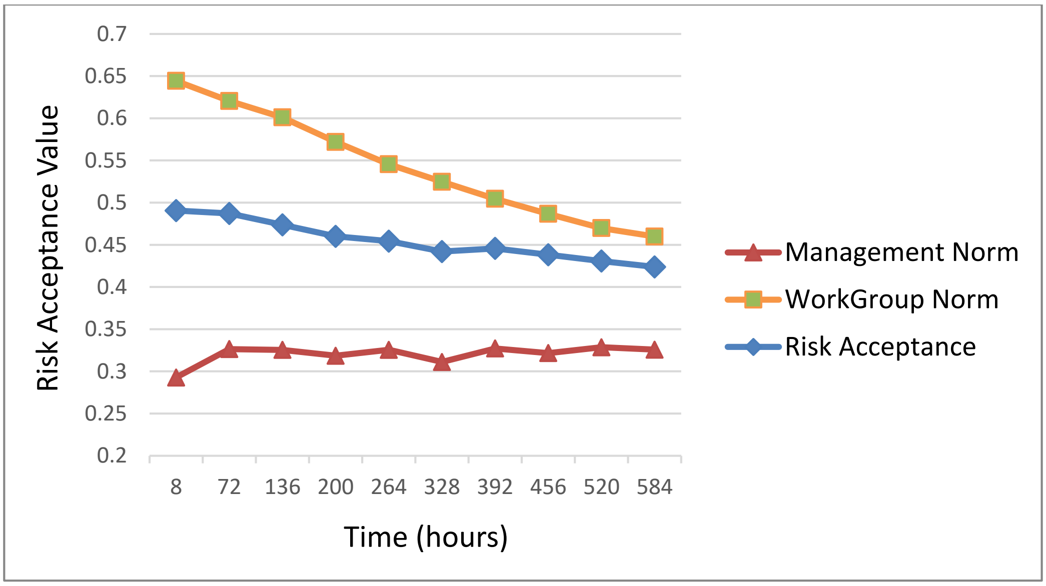


Figure 21 – Change in the risk acceptance of management and workgroup and the individual risk acceptance in the baseline model

Moreover, Figure 22 shows a positive and significant relationship between personal risk attitude and the risk acceptance (r2=0.666, p<0.001) in the baseline model, such that the risk acceptance increases with the increase of the risk attitude (when the worker has a more risk-seeking attitude). These results reasserted the findings of many previous empirical studies about the effect of personal attitude on safety behavior (Ajzen, 1991; Donald & Young, 1996; Teo et al., 2005; Cavazza & Serpe, 2009; Shin et al., 2014; Xu et al., 2018).

Liang et al. (2018), in their study on the social contagion within the construction crew, found that workers are more inclined to violating safety regulations when they are socially supported to do so by their coworkers. In other words, workers who identify high levels of coworkers' safety violations are more likely to breach safety regulations themselves. Moreover, the empirical results of the study by Choi et al. (2016) showed that the safety behavior of workers is affected by both management and workgroup norms. Figures 23 & 24 show the relationship between management norm or the

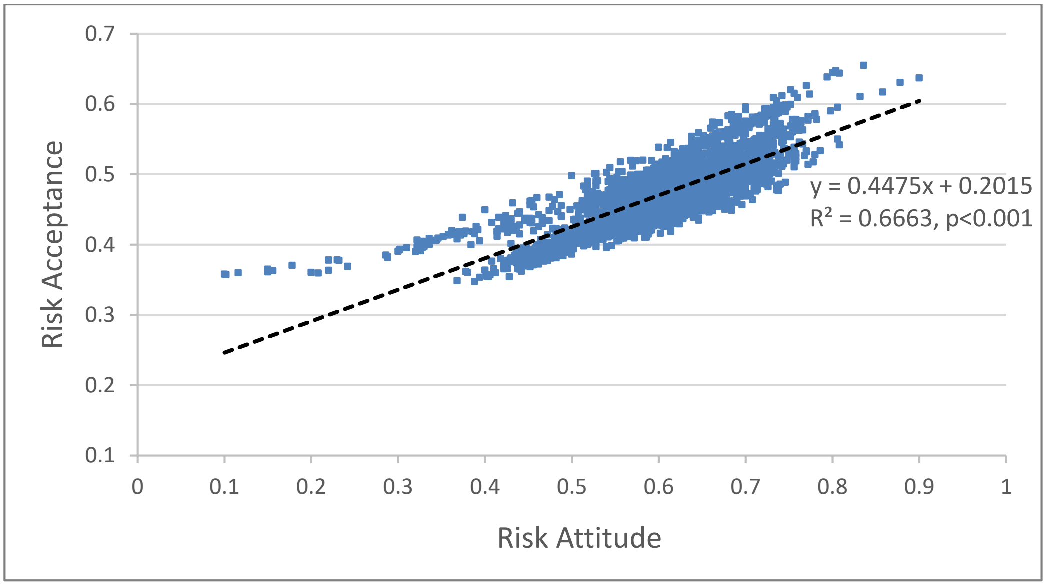


Figure 22 – Relationship between risk attitude and risk acceptance in the baseline model

workgroup norm and the individual risk acceptance respectively, in the baseline model. As shown in both graphs, there is a positive relationship between the subjective norm and the risk acceptance, such that when the strictness of these norms increases (when the values of the norms are smaller) the acceptable risk by the worker decreases and thus the safety behavior improves. These results again reiterate the findings of the studies mentioned above. Furthermore, Choi et al. (2016) in the same study, found that a workers' social identification with the project strengthens the relationship between management norms and safety behavior whereas it weakens the relationship between workgroup norm and safety behavior. This is directly reflected in Figures 23 & 24. As shown in Figure 23, the regression slope of the interaction between management norm and the risk acceptance is steeper when there is higher identification exhibited by the workers towards the project. On the other hand, Figure 24 shows the opposite since the slope becomes steeper when there is low identification with the project by the workers.

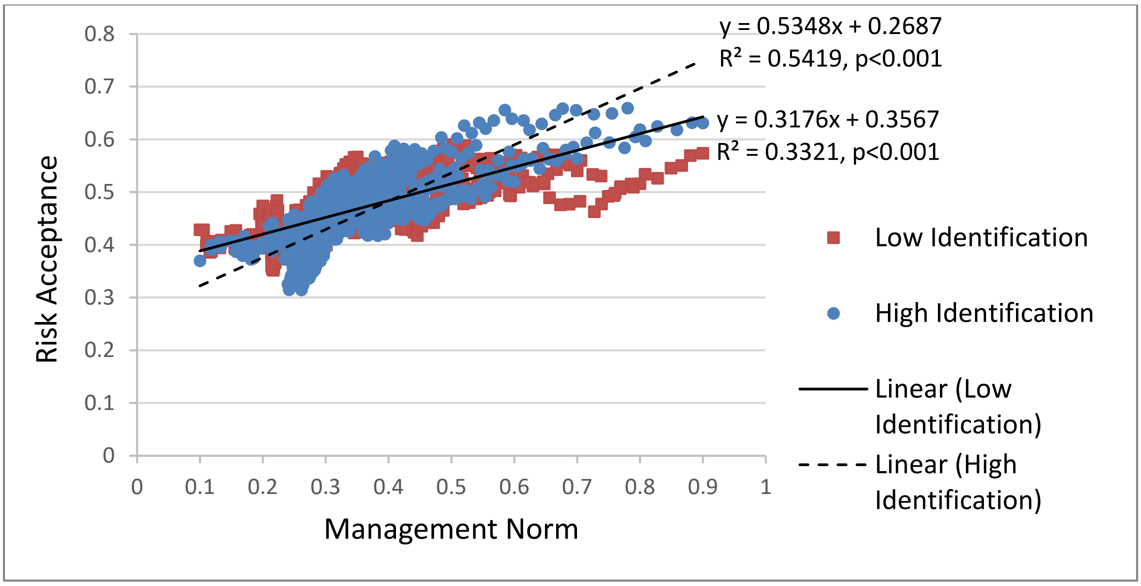


Figure 23 – Interaction between project identity and management norms in the baseline model

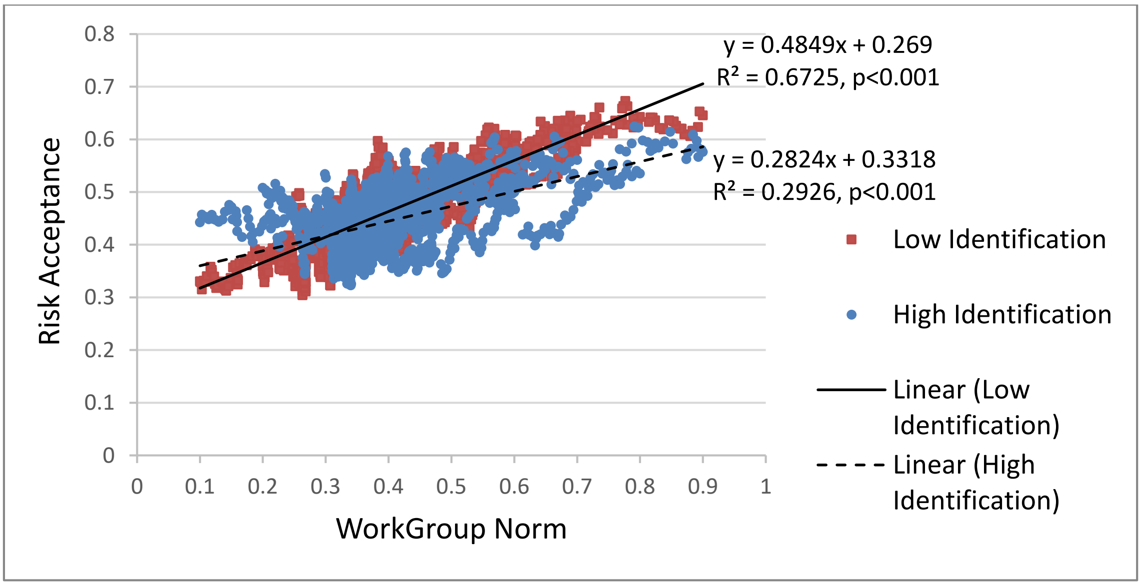


Figure 24 – Interaction between project identity and workgroup norms in the baseline model

Second, in order to check the quantitative conformity of the replicative validity, the baseline model was run 50 times and the means for two important indicators were calculated. The first indicator is the ratio of unsafe behavior. The mean of the unsafe behavior ratio from the 50 runs is 0.31 (standard deviation = 0.0157). This result is in compliance with Sa et al. (2009) and Fang & Wu (2013), where both studies indicated that usually one third of the workers behaved unsafely on a construction site. The second indicator used in the incident rate. The incident rate was calculated based on the Heinrich triangle (Heinrich, 1959). Heinrich suggested that for every major accident there are 29 minor accidents and 300 near misses. This means that the ratio between major injuries, minor injuries and near misses was 1:29:300 or 30:300 between accidents and near misses. The mean of the incident rate from the 50 runs is 3.9 (standard deviation = 0.96) which is similar to the incident rate of nonfatal occupational injuries in the construction industry in 2015 which is equal to 3.5. (USBLS 2016).

CHAPTER 7

ANALYSIS AND DISCUSSION OF RESULTS

7.1 Safety Performance Indicators

In order to study the effect of the use of a safety inspector versus the use of a UAS on the safety performance of a construction site, three types of indicators were used. As a first step, the baseline model was used to calculate the indicators. All variables and parameters were initialized as mentioned earlier in chapter 5.

7.1.1 *Incident Rate*

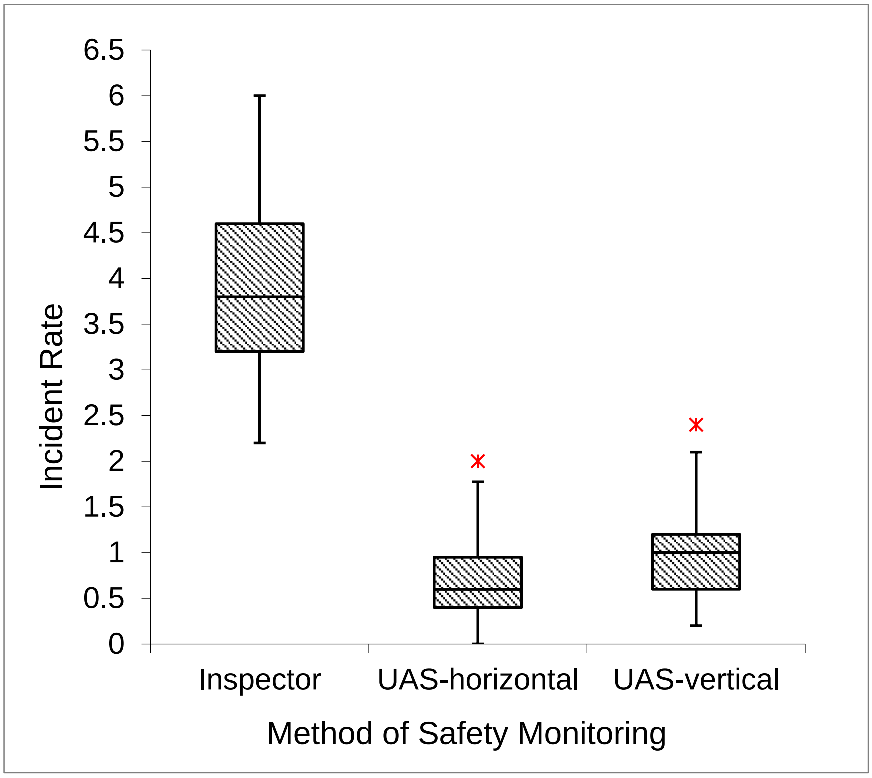
The first indicator used is a lagging indicator which is the incident rate. Equation 13 is used to calculate the incident rate and it is adopted from OSHA:

$$\text{Total Recordable Incident Rate} = \frac{\textit{Number of recordable cases} * 200{,}000}{\textit{Number of total labor hours worked in the year}} \tag{13}$$

(Jazayeri & Dadi, 2017).

Three cases were considered: (1) employing a safety inspector for safety monitoring (2) using a UAS for safety monitoring in a horizontal-type project (3) using a UAS for safety monitoring in a vertical-type project. Moreover, in order to get reliable results, the model was simulated 100 times for each case.

Figure 25 shows the box plots for the incident rate for the 100 simulation runs in each of the cases under study. Moreover, the table shows the mean for the incident rate for the 100 runs. The mean for the incident rate for the case of the safety inspector is 3.9. As for the case of the UAS in horizontal projects, the mean is 0.63 which is significantly less than the previous case. Finally, the mean for the incident rate for the case of a UAS in vertical projects is 0.98 slightly greater than for horizontal projects but still mush less than the case of the safety inspector.



Method	Inspector	UAS-horizontal	UAS-vertical
Mean	3.9	0.63	0.98

Figure 25 – Box plots and the mean for the incident rate of 100 simulation runs

7.1.2 *Safety Behavior*

The second indicator is the safety behavior of workers which is a leading indicator. The safety behavior of workers is inspected by tracking the change in the ratio of unsafe behavior with the progress of the project. The unsafe behavior ratio is calculated as shown in Equation 14:

$$\text{Unsafe Behavior} = \left(\frac{Total\ observed\ unsafe\ behavior}{Total\ observed\ safe\ behaviour + Total\ observed\ unsafe\ behavior}\right) * 100 \quad (14)$$

(Nasirzadeh et al., 2018).

Figure 26 shows the change in the unsafe behavior ratio with time. The data points are the average of 100 iterations. The horizontal axis represents the time in hours in the simulation, bearing in mind that each 8 hours constitute one day, and the vertical axis represents the ratio of unsafe behavior in percentage. The results show that the unsafe behavior of workers increases with time in the case of the safety inspector. The inspector needs around 3 hours to complete one inspection and this inspection is being conducted only once per day. Moreover, the site conditions change twice per day and accordingly the behavior of workers relative to these changes will also be modified. This means that the inspector will be able to detect only limited numbers of the unsafe behavior by workers. For instance, assuming that the inspection is being conducted in the morning, most of the unsafe behavior of the workers during these 3 hours will probably be detected. However, all modified conditions and unsafe behavior during the remaining 5 hours of the day will be missed. Accordingly, the obtained result is explained by the fact that the workers are rarely getting warned about their unsafe

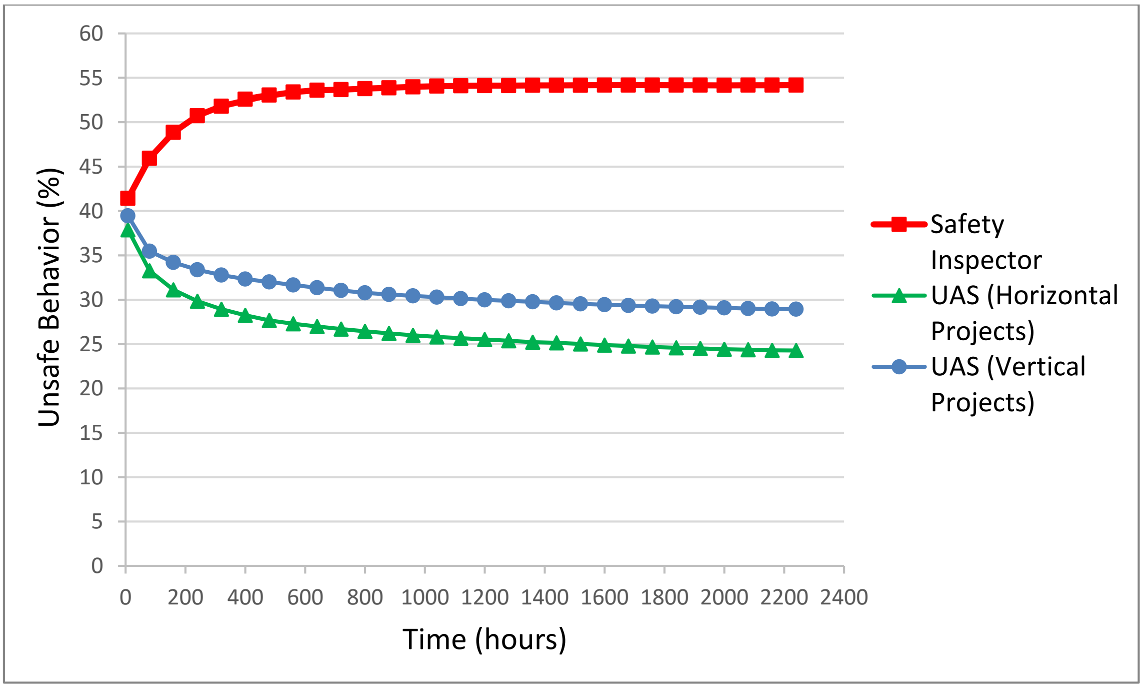


Figure 26 – The effect of intervention type on the safety behavior of workers

behavior and this is why they resume to act unsafely. This clearly shows that employing a safety inspector to monitor the site conditions is not enough on its own to improve the behavior of workers. It should be accompanied with other safety management practices, such as safety training, toolbox meetings, feedback, and open communication about safety.

For the case of the use of the UAS, the unsafe behavior for both horizontal and vertical type projects decreases at a fast rate in the beginning up till around 200 hours or 25 days, and then this rate decreases gradually until the curve levels out towards a minimum value at around 1200 hours or 150 days. This is due to the fact that at the beginning three factors are all contributing together to the change in the risk acceptance of the worker: the personal risk attitude, the communication within the workgroup between workers, and the communication with management through the UAS. However, towards the end of the simulation, the effect of workers on each other is minimized since most of the workers will have reached a unified or similar value of perceived workgroup norm, bearing in mind that the study is done on the same work crews throughout all the simulation. For instance, five random workers were chosen and their individual unsafe behavior ratio plotted over time. As shown in Figure 27, the curves of the workers' individual safe behavior tend to converge until they reach similar values where they become steady. Moreover, since towards the end of the simulation, the unsafe behavior of the worker will have decreased, then they will not get a high chance of updating the risk acceptance through management intervention. Finally, it is impossible for the attitude of the workers to decrease infinitely with time and this is controlled in the model by setting upper and lower boundaries for the value of the attitude variable. This fact also effects the rate of decrease of the unsafe behavior.

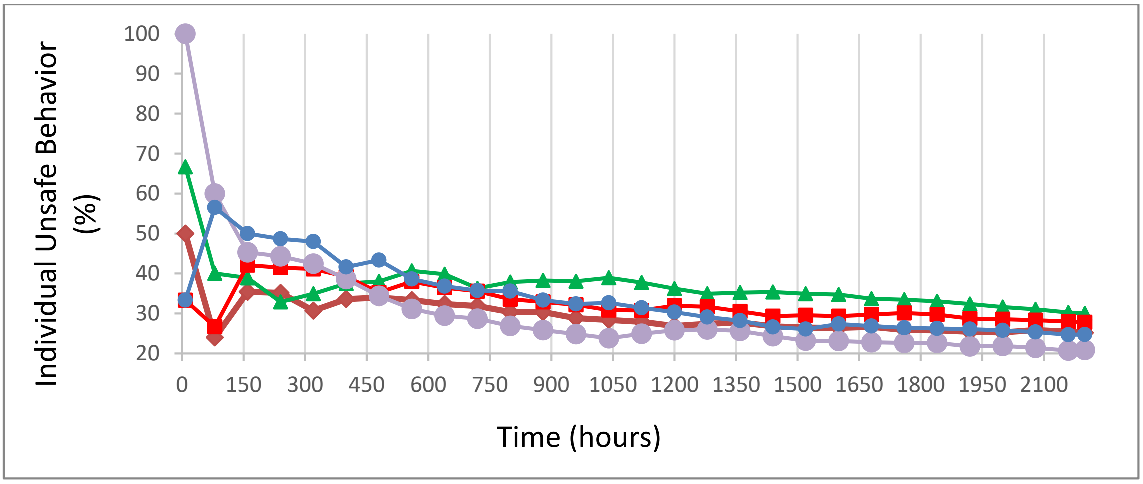


Figure 27 – Change of the individual safety behavior of workers

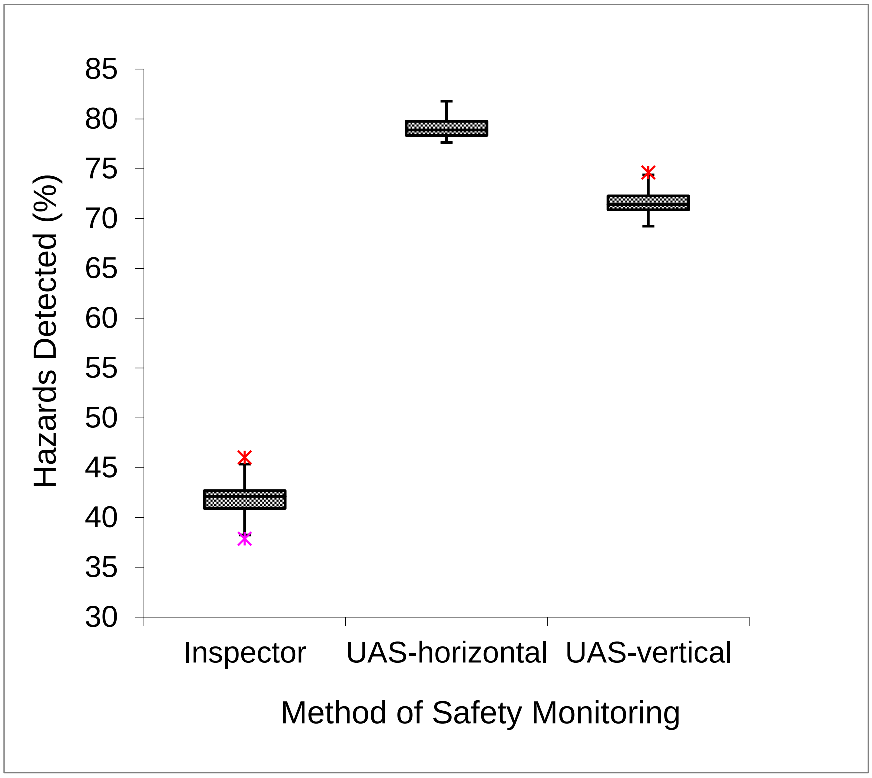
Although the two curves in Figure 26 for horizontal and vertical projects show the same trend, the decrease is greater for horizontal projects. In horizontal projects, the total decrease from beginning to end is 13.61% while in vertical projects the decrease is 10.52%.

7.1.3 *Hazards Reported*

The third indicator used is also a leading indicator which is the number of hazards reported. This indicator shows the percentage of unsafe conditions that were detected throughout the project. It is calculated using Equation 15.

$$\text{Hazards Reported} = \left(\frac{\textit{Total hazards detected}}{\textit{Total number of hazards}}\right) * 100 \tag{15}$$

Figure 28 shows the box plots for the % of hazards detected in 100 simulation runs for each of the cases under study. Moreover, the table shows the mean for the % of hazards detected from the 100 runs. The mean for the case of the safety inspector is 41.88%. The low percentage of hazards detected in the case of the safety inspector explains further the reason behind the increase in the percentage of unsafe behavior of workers instead of decreasing since a similar percentage will be obtained for the ratio of unsafe behavior that were detected by the inspector.



Method	Inspector	UAS-horizontal	UAS-vertical
Mean	41.88	79.07	71.64

Figure 28 – Box plots and the mean for the % of hazards detected of 100 simulation runs

For the case of the UAS, the mean is 79.07% for horizontal-type projects and 71.64% for vertical-type projects. The fact that the percentage of unsafe conditions detected by the UAS is very high despite the restrictions imposed (visualization & detection by algorithm) is highly related to the number of times that the cell conditions change per day. For instance, as mentioned earlier, the “changeCond” event is set to be triggered twice per day, meaning twice every 8 hours. As obtained from the simulation model, the inspection mission, including the time taken by the algorithm to apply the detection, takes around 45 minutes. This means that while the conditions will change only 2 times in the 8 hours, the UAS will have conducted around 8 missions in this time duration. So if an item was not visualized or detected in the first mission, for example, there is a good probability that it will be visualized or detected in the next mission or the next before the condition actually changes. This is to some extent a true reflection of reality depending on how dynamic the site is. This is because, if the UAS fails to clearly inspect a certain area, it can be sent again for inspection when and as much as needed before the conditions in this area change. However, in order to understand further the implications of this issue on the safety performance, the model was tested under different trigger values for the event "changeCond". The details for this experiment are elaborated in the next section.

The results of the three calculated indicators show that when considering the intervention of safety monitoring independently, the use of a UAS will yield a considerably better safety performance when compared to the use of a safety inspector. The two leading indicators, safety behavior and hazards detected, explain the results of the lagging indicator which is the incident rate. When using the UAS, the safety behavior of workers improves progressively which implies that the attitude of workers towards safety improves such that they become more risk-averse and thus will avoid taking risk in unsafe conditions. Moreover, the high percentage of hazards detected implies that these conditions are being treated and that workers will be less subject to unsafe conditions which will in turn yield to safer behavior. The correlation of these two factors directly implies that less incidents will occur in the project since the project will contain less unsafe conditions and since workers will behave more safely. For the case of the inspector, the increase in the unsafe behavior of workers is the main factor that explains the high rate of incidents which is in turn affected by the low percentage of hazards being detected since in this case the workers will be subject to more unsafe conditions.

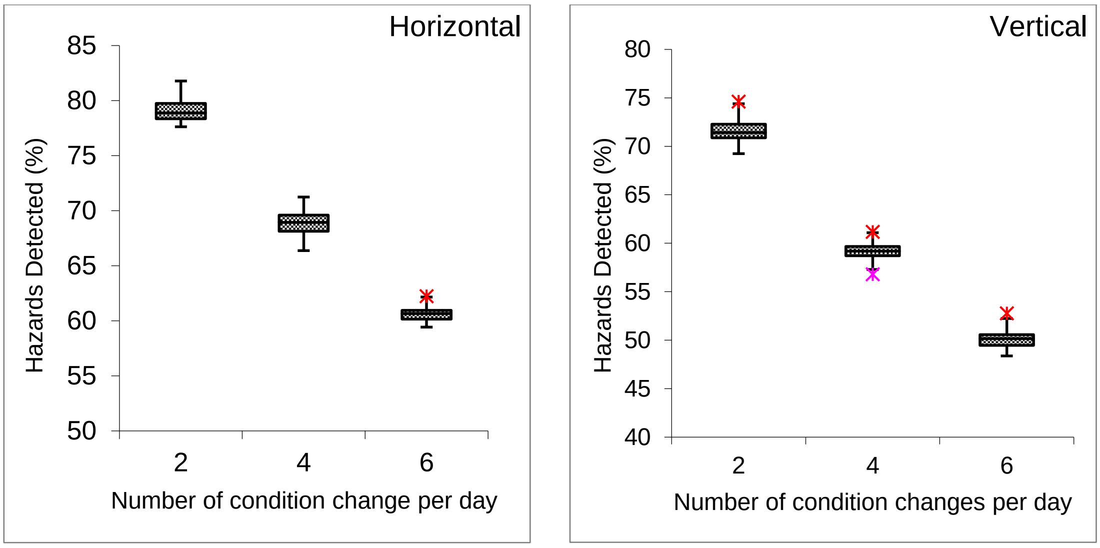
Moreover, the results prove that the nature of the project (horizontal vs vertical) effects the performance of the UAS. The use of a UAS yields a better safety performance in horizontal type projects. This technology, for example, can prove to be very beneficial for projects such as bridges, highways, dams, etc. The performance of the UAS in vertical type projects is affected by factors such as: the limited altitude that can be reached by the UAV as indicated by the law which restricts the view of all the building and mainly the roof works, the protecting net that may cause a barrier against detailing, and the strong winds at heights that may affect the stability of the drone.

7.2 Simulation Experiments and Results

In order to understand the effect of the characteristics of the project on the performance of the UAS, several experiments were formulated. Note that since the main aim of the study is understanding the behavior of the UAS, these experiments are only conducted on the case of the use of a UAS for safety monitoring.

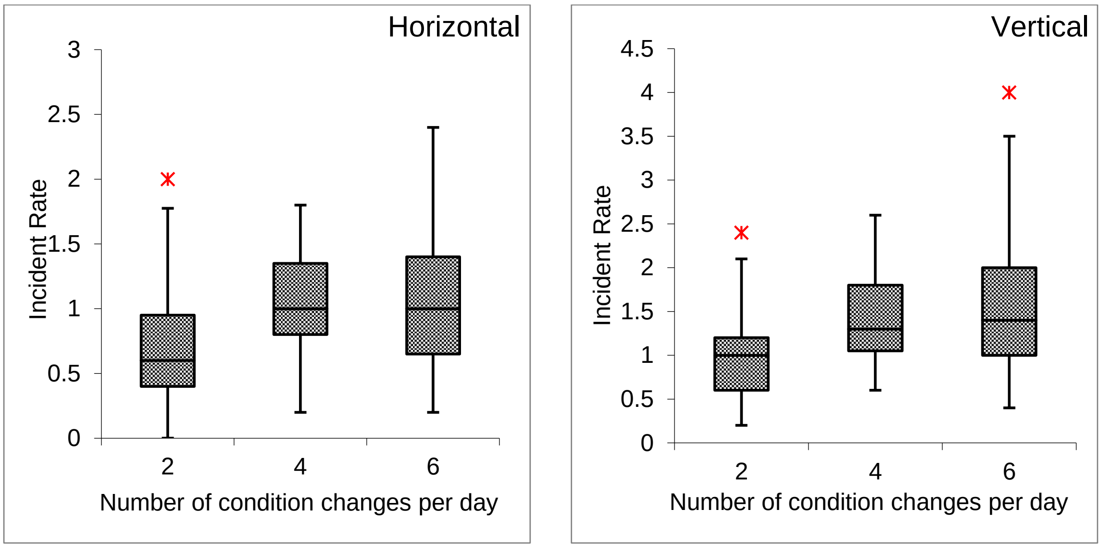
7.3.1 *Effect of Dynamicity*

First, the effect of the dynamic nature of the project was inspected by modifying the number of change of conditions per day or in other words the number of times in which the event “changCond” is triggered (2, 4, or 6 changes per day). The three indicators were tested under these conditions for both horizontal and vertical type projects. Figure 29 shows that as the number of changes per day increases (an increment of 2 each time), the % of hazards detected decreases around 10%.



Number	2	4	6
Mean	79.07	68.85	60.61

Number	2	4	6
Mean	71.64	59.2	50.13



Number	2	4	6
Mean	0.63	1.02	1.08

Number	2	4	6
Mean	0.98	1.41	1.49

Figure 29 – Effect of the number of changes of site conditions per day on the incident rate and the % of hazards detected in horizontal & vertical type projects

Moreover, Figures 30 & 31 show that the safety behavior of workers is also affected by this variation. As the number of changes per day increases, the rate of decrease in the unsafe behavior of workers decreases considerably. For instance, in horizontal type projects, 2 changes per day yield a total decrease of 13.61% while 6 changes per day yield a total decrease of 7.26% only. For the case of vertical type projects, the effect is even more intensified because for the case of 6 changes per day, the unsafe behavior of workers actually increases with a total change of 1.97%. Figure 29 also shows that the incident rate increases with the increase of the number of changes per day. However, it is interesting that as the number of change per day increases, the rate of change in the incident rate decreases. For the case of the horizontal project, for example, the mean of the incident rate increases from 0.63 to 1.02 between 2 and 4 changes but only changes from 1.02 to 1.08 between 4 and 6 changes. This is explained by the fact that when the conditions of the site change more frequently, this means that the time that the worker is exposed to an unsafe condition decreases and accordingly the probability that an incident occurs also decreases. This contrast between the high probability of occurrence of the incident due to the increasing unsafe behavior of workers and the low probability of occurrence of the incident because of the short time of exposure of the worker to the unsafe condition also explains why the distribution of results for the case of 6 changes shows more variability than the distribution of results for the case of 4 changes.

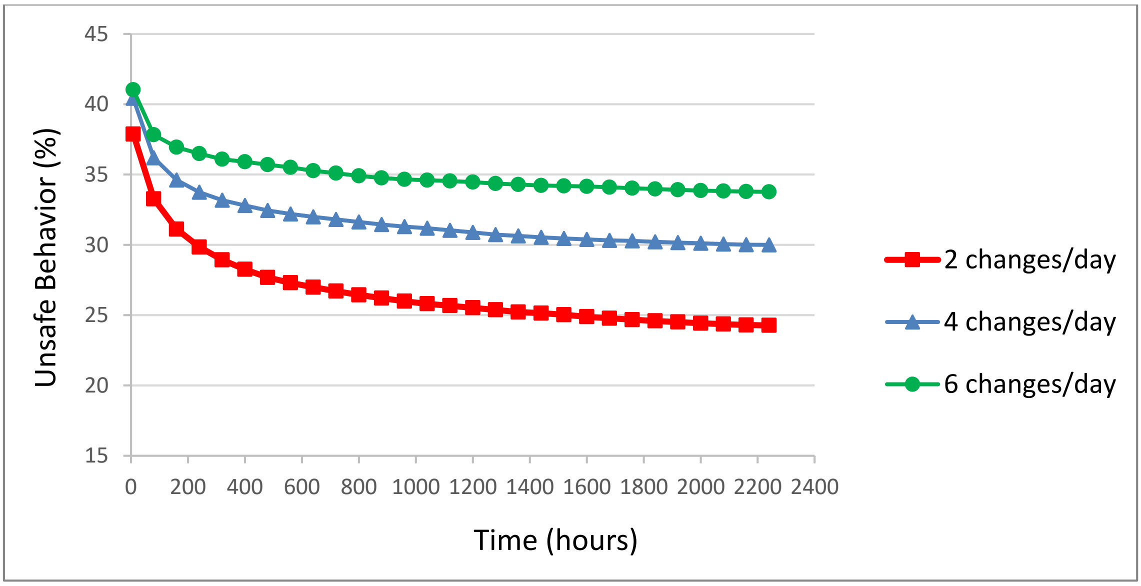


Figure 30 – Effect of the number of changes of site conditions per day on the safety behavior of workers in horizontal type projects

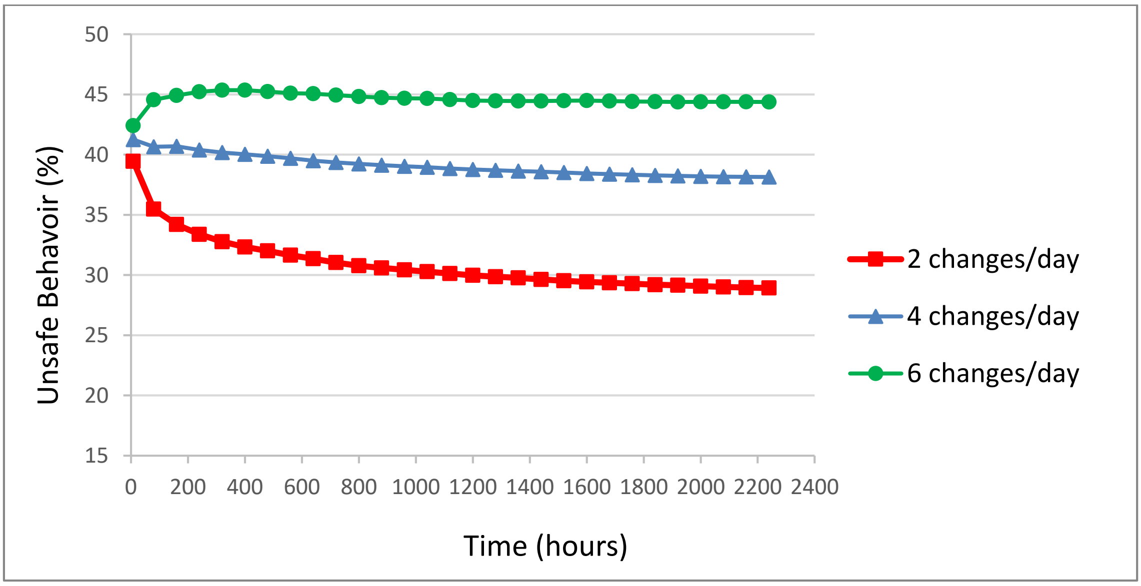


Figure 31 – Effect of the number of changes of site conditions per day on the safety behavior of workers in vertical type projects

7.3.2 *Effect of Site Risk*

Second, the effect of the level of risk in the project was studied by modifying the site risk. The model was run under three scenarios: (1) low risk site conditions (2) moderate risk site conditions (baseline), and (3) high risk site conditions. As mentioned earlier, the site risk reflects the level of risk present on site. This attribute is used as a main characteristic of the project since in reality construction projects are not similar in terms of the probability of occurrence and the severity of the unsafe conditions that workers may be subject to. For instance, different construction trades and activities impose different levels of risk on workers (Choe & Leite, 2016). As such, even within the same project the risk can differ in different periods or phases of the project (Esmaeili & Hallowell, 2012). The low risk site is represented in the model with 25% probability and the high risk site with 75%. As for the severity of the risk, same as the moderate risk condition, the beta distribution ranging from 0 to 1 is assigned for the variable "ActualRisk". However, the average severity is 0.25 (positively skewed distribution) for low risk site condition, 0.5 for moderate risk site condition, and 0.75 (negatively skewed distribution) for high risk site condition (Choi & Lee, 2017).

For this experiment and the next, only the safety behavior of the workers will be studied since the initial conditions that are being modified will affect the final values of the incident rate regardless of the safety monitoring method used. This is why it would be difficult to understand whether the change in the incident rate is due to the initial condition or the monitoring method. Conversely, the fact that we are able to monitor the change of the unsafe behavior from the beginning towards the end, this change can be justified.

As shown in Figure 32, the use of the UAS is mostly effective for the case of high risk site conditions where the unsafe behavior decreases a total of 21.58% to finally reach 13.38% unsafe behavior. For the case of moderate site risk there is 13.61% decrease and the final value reached is 24.26%, and finally for the case of low site risk, the decrease is minimal and equal to 5.73% to eventually reach 27.17%. It is important to note that the final values of unsafe behavior reached in both the modest and the high site risk are smaller than the final value reached in the low site risk. This is because in low risk sites, workers will not get a big chance of improving their attitude since the number of situations where they will be susceptible to risk is already very low.

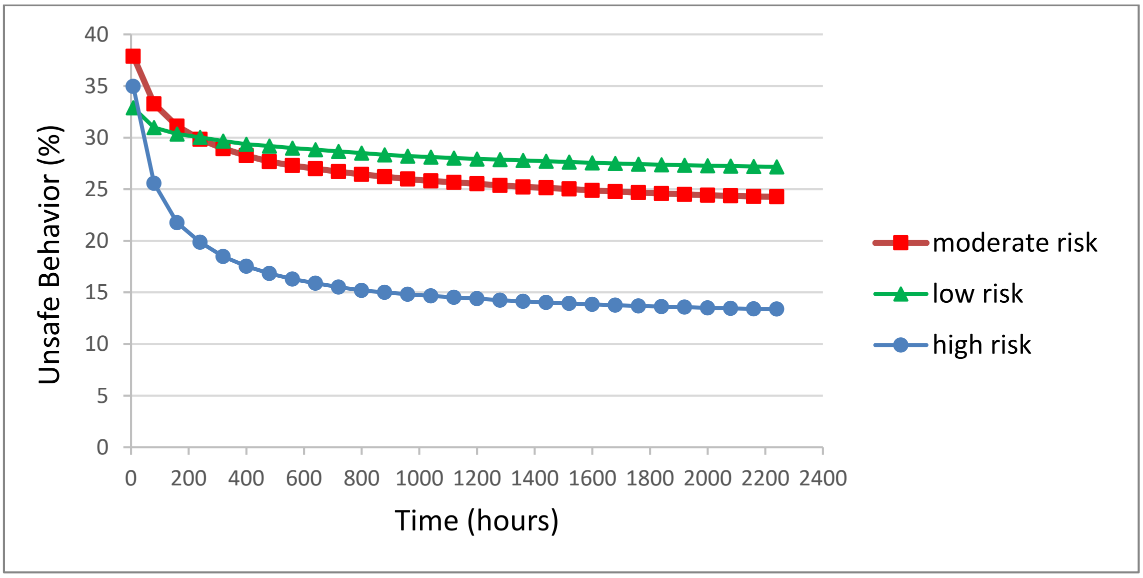


Figure 32 – Effect of the site risk on the safety behavior of workers when employing a UAS in horizontal type projects

7.3.3 *Effect of Safety Attitude*

The third experiment is related to the initial attitude of the workers. This attribute highly reflects the safety culture of an organization. Safety culture relates to the organization's shared beliefs, values, attitudes and norms associated with safety, from management down to every single worker (Leino et al., 2010). So in our case a low attitude (range considered between 0.1 and 0.5) suggests a strong safety culture where workers prioritize safety and hold themselves responsible towards their own and their coworkers' safety as well. As for the case of high attitude (range considered between 0.5 and 0.9), this suggests a weak safety culture where workers do not value the importance of safety and have a high tendency to taking risk. Figure 33 shows that the use of a UAS as a safety monitoring method has a minimal effect on the safety performance of projects that have a strong safety culture. This is due to the fact that the attitude of workers towards safety is already good and it would be difficult to improve it even further. On the other hand, a significant decrease in the unsafe behavior is noticed in the case of projects with a weak safety culture since the attitude of workers towards safety can be greatly improved. It is also shown that the two cases end up with the same percentage of unsafe behavior at the end of the project.

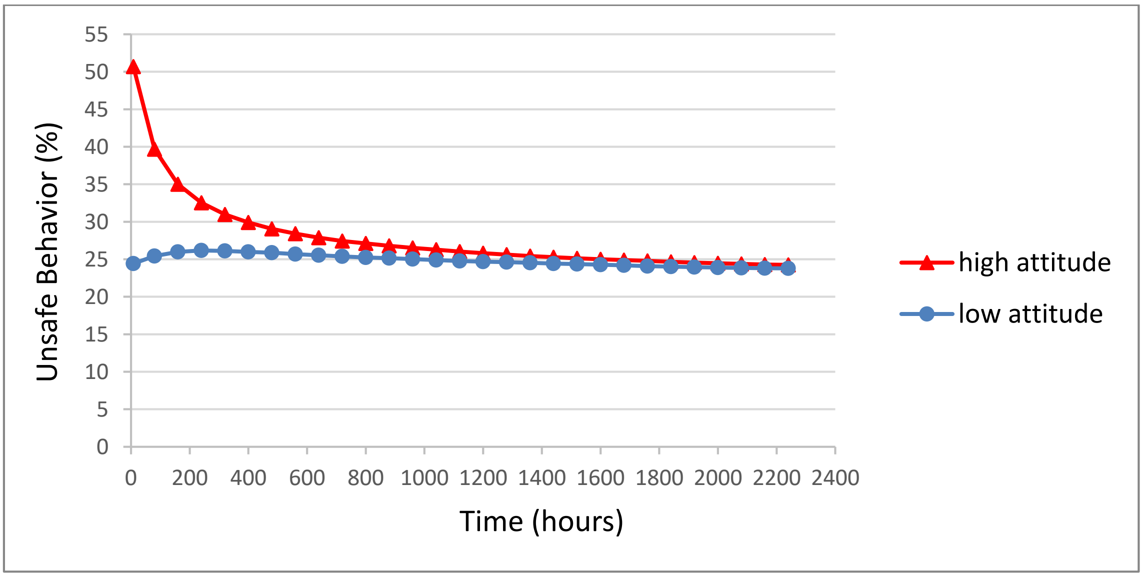


Figure 33 – Effect of the safety culture on the safety behavior of workers when employing a UAS in horizontal type projects

The last two experiments suggest that for the cases of low site risk and a strong safety culture, the use of the UAS alone does not present a very tempting investment for project managers. However, the comparison of the results with the case of the safety inspector puts things into a different perspective. In both Figures 34 & 35, the unsafe behavior of workers increases with time in the case of the safety inspector. Especially for the case of strong safety culture, the unsafe behavior of workers increases around 27% since the unsafe behavior of workers is highly connected to their safety attitude. This is due to the fact that the attitude of workers doesn't simply remain constant. Even if they start off with a good safety attitude, the lack of the appropriate follow-up procedures by management will lead back to an inclination in the overall safety performance.

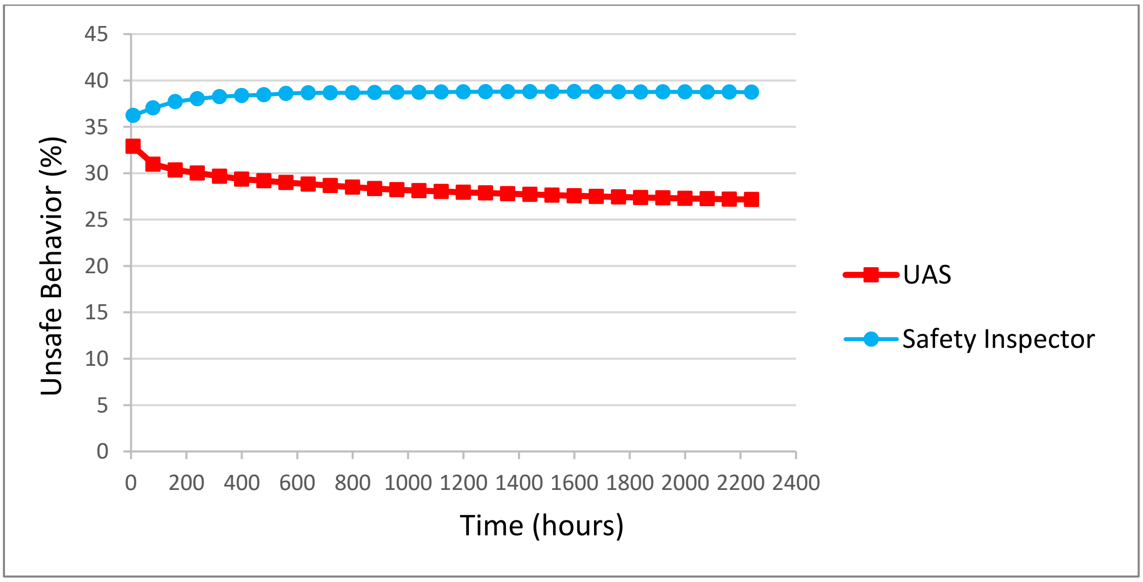


Figure 34 – Change in the safety behavior of workers in low risk sites when employing a safety inspector versus a UAS

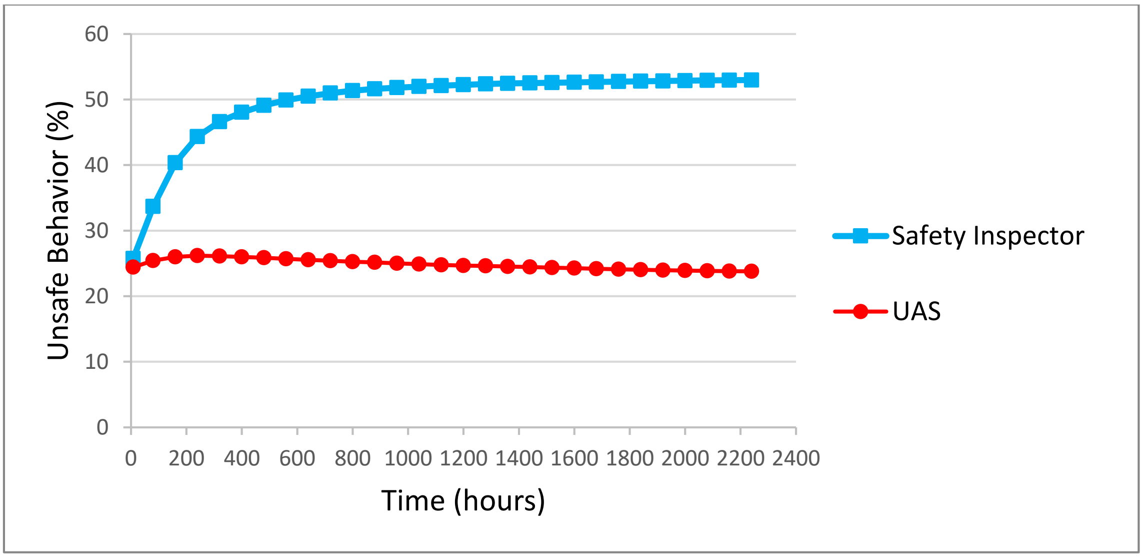


Figure 35 – Change in the safety behavior of workers in projects with strong safety culture when employing a safety inspector versus a UAS

CHAPTER 8
CONCLUSIONS AND RECOMMENDATIONS

The construction industry is known for its highly hazardous nature and elevated injury rates. The two main reasons for accidents discussed in the literature are unsafe conditions and unsafe behavior and acts by construction workers. Therefore, a standardized observation system on site is necessary in order to monitor and improve the safety performance. The traditional practice of safety monitoring by a safety inspector who travels around the site is tedious, impractical and time consuming. In an attempt to overcome the limitations and difficulties of this practice, researchers recently started exploring the use of drones or UAVs as safety monitoring tools. The application of this technology for safety monitoring is still emerging. In fact, the use of an Unmanned Aerial System on an actual construction site for the purpose of safety inspection has been scarcely documented in the literature. Therefore, this study aimed at studying the long term influence of using this system on the safety performance of construction sites compared to the traditional practice of safety monitoring by a safety inspector. This was achieved by preparing an agent-based model that simulated the dynamics of a real construction site while taking into consideration the cognitive process of construction workers' safety behavior in combination with the safety management intervention. The contribution of this study lies in providing practitioners and project managers with some guidance in choosing the appropriate safety system that can provide a continuous evaluation measure for the safety conditions and acts on site for the aim of improving these conditions and minimizing the number of incidents.

After attaining a deep understanding of construction workers' safety behavior and the components and behavior of the unmanned aerial system through a meticulous literature review, a conceptual framework was prepared. The framework illustrated the cognitive process of workers' safety behavior which is directly related to the risk perception and the risk acceptance by workers. The risk acceptance is determined by both internal factors of the worker such as attitude, as well as the interaction with external factors such as other coworkers, representing the workgroup norm, and the safety inspector or the drone, representing the management norm. The comparison between the perceived risk and the acceptable risk by the worker will lead to the decision of safe or unsafe behavior. Regarding the UAS, the basic behavior is adopted from the study by de Melo et al. (2017). A safety checklist for the mission is prepared before the start of the inspection. The drone follows a predefined path and the inspection is done on three different levels: Overview, medium altitude view, and close up view. For each level, there are specific safety requirements intended to be inspected. The detection of the safety requirements is done automatically through an installed detection algorithm in the system. Additional attributes of the UAS that were taken into consideration are the speed of the drone and the battery life. Moreover, the project is characterized by the level of risk and whether the project has a horizontal or vertical nature.

After translating the conceptual model into the agent-based model, the computerized model is verified and its' results validated qualitatively and quantitatively by comparing these results with empirical findings from previous studies. Finally, simulation runs and experiments are conducted. The results showed that the use of a UAS can effectively improve the safety performance of both horizontal and vertical type projects. However, the performance of the UAS is restricted by factors such as altitude limits and wind speed in vertical type projects. Moreover, the conducted experiments showed that as the project becomes more dynamic, the performance of the UAS becomes less efficient in the improvement of workers' safety behavior, especially in vertical type projects, while preserving an almost steady incident rate. Finally, the use of the UAS yields best results in high risk projects and projects with a weak safety culture.

This study imposes several practical implications and recommendations that aim to enhance the safety management of construction projects. Since studies related to the actual application of a UAS on construction sites and the effect on the improvement of safety performance are currently scares in the literature, this study aimed to fill this gap by studying this issue through agent-based modeling. The results provide practitioners with an idea of the advantages of the use of such a system on improving the workers' safety behavior, increasing the amount of unsafe conditions detected, and ultimately decreasing the incident rate within their organization. Moreover, project managers have the chance to evaluate the safety management practices they already use and understand based on the type of project and the level of risk in each phase of the project whether employing the UAS can add value to their system. Note that it would be useful, in order to make additional use of these results, to perform a cost analysis related to the components of the UAS. Managers should keep in mind when taking this step that this technology is an investment that can be used on several sites using the same equipment which are already low in purchase and maintenance cost. However, the use of the UAV as an equipment on its own is not enough. The UAV is part of a full system that includes the employment of human resources such as trained and experienced pilots for the UAV and staff with enough safety knowledge in the project for efficiently planning and observing the flight missions. Restrictions against the appropriate use of the technology include: country legislation, weather conditions such as wind and rain, physical obstacles such as electrical wires, poles and trees, and limited view of internal areas. However, if employed correctly, this system can bring about great benefits to the safety performance of the organization, not just because it highly facilitates the process of observation and monitoring but also because it helps in collecting a valuable database that can be used for risk analysis, performance evaluation, and root cause analysis which all in turn help the organization in continuous improvement in the area of safety management.

Finally, several limitations of this research study are worth mentioning so that future research work can be recommended. Regarding the developed agent-based model, the major limitation is the use of a uniform distribution when describing certain behavior attributes of the workers since no info in the literature is present regarding these distributions. In this study, identifying such probability distribution which requires a separate research study is out of the scope. Regarding the conceptual framework, the model only considers the inspection of the project externally. The use of a UAV in indoor spaces has totally different characteristics and considerations and the behavior of the UAV differs completely. This issue can be considered in future studies. Moreover, it is important to note that in reality, safety inspectors tend to take shortcuts in order to reach the locations where construction activities are taking place instead of actually traversing the whole site, and thus the actual time needed to inspect the site might be less than the time considered in the model. This study can be extended further by collecting real information from construction sites regarding all assumed variables in order to further validate the model. Furthermore, it would be interesting to back up the study with cost analysis and comparison between the use of a safety inspector and a UAS for safety monitoring.

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