Studying the Impact of UAVs Adoption on the Safety Performance of Construction Projects Using Agent-based Modelling

Abstract

Despite recent improvements in construction safety, this industry remains one of the major contributors to the number of work-related injuries and fatalities. Unsafe site conditions and unsafe behavior by workers are the two main reasons behind accidents and accordingly these two factors should be continuously monitored. The traditional practice of safety inspection by a safety officer who navigates the site is very tedious and time consuming. Drones or unmanned aerial systems (UAS) can be used to aid in this process since they can fly around the site collecting assets rapidly and frequently and can reach limited-access locations. The use of this technology in construction is still new and studies related to the employment of UASs on actual construction projects for safety monitoring are scarce in the literature. Therefore, this study employs agent-based modeling to examine the effect of the adoption of drones for safety inspections on the safety performance of construction sites compared to the traditional practice. The safety performance is evaluated using three types of indicators: incident rate, safety behavior, and hazards reported. The results show that at the end of one year, the mean incident rate is 3.9 in the case of the inspector and 0.63 with the UAS. Moreover, during this year, 42% of hazards were detected by the inspector versus 79% by the UAS. Finally, a total decrease of 13.6% in the unsafe behavior of workers is observed with the UAS, while an increase in the unsafe behavior is noticed in the case of the inspector. The study contribution lies in providing safety managers and practitioners with a preliminary idea about the practical benefits of drones when used for safety monitoring.

Keywords: agent-based modelling, construction safety, safety inspector, safety performance, unmanned aerial system

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 [1]. The reasons behind accidents on construction sites are mainly attributed to unsafe conditions and unsafe acts [2]. A standardized observation system for these conditions on site is necessary to monitor and improve the safety performance [3]. Unfortunately, the common practice of safety inspection by walking around the site is a very time consuming and tedious process [4], especially in large and complex building projects as well as heavy civil construction projects.

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 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 [5]. The use of a UAS 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 modelling 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 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 minimizing the number of accidents and near misses.

1.1. Safety in Construction

Reference [6] indicated that all accidents occur due to unsafe conditions or unsafe acts. 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 [7]. According to [8], workers exhibit unsafe behavior either due to lack of knowledge or due to poor safety attitudes. 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.

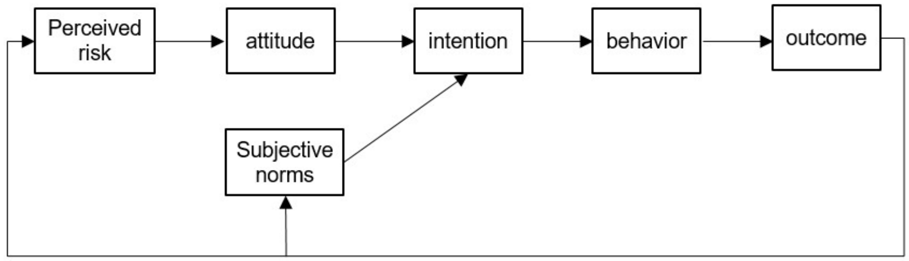

Fig. 1. Workers' mental process in relation to their safety behavior [6,8,10]

As shown in Figure 1, the theory of planned behavior traces back behavior to behavioral intentions which are affected by factors such as the attitude of the worker and the subjective norms [9]. The safety attitude of a worker is developed through the perceived risks that this worker acquires from diverse sources [7]. Risk perception is defined as "the subjective judgment that people make about the characteristics and severity of a risk" [9]. Subjective norms represent "a person's perceptions of significant others' expectations of his behavior" [11]. For the case of construction workers, significant others are co-workers and management [11]. 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 [7].

1.2. Safety Performance and Indicators

Lagging indicators such as the Total Recordable Incident Rate show the magnitude of the occurrence of accidents and are reactive in the sense that they collect after the fact statistics. Although these indicators are easy to collect and easily understood [12], they don't provide any insight about the specific items that should be addressed in the system to improve this performance [13]. The need for more proactive safety measures lead to the introduction of leading indicators for the measurement of safety performance. These indicators provide metrics for monitoring the process during its implementation and thus giving the chance for managers to proactively respond to the collected results [13]. Ideally, a combination of both lagging and leading indicators should be used to measure the safety performance. In the current study, safety behavior and hazards reported will be used as leading indicators, while incident rate will be used as lagging indicator.

1.3. Unmanned Aerial Systems for Safety in Construction

Unmanned aerial vehicles (UAV) 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 [5],[14]. The drone can collect visual assets 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 [5],[15]. Managers can get the chance to constantly visualize dangerous activities without physically being present at the location. Reference [15] 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.

Reference [5] 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 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 [5]. Moreover, drones can be equipped with communication devices for direct interaction [15].

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)" [15],[14]. Reference [16] 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.

1.4. Agent-based Modelling

The construction industry is known for being very dynamic and evolving such that frequent changes have become a rule instead of an exception. 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 agent-based modelling. Agent-based 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 [17]. In the area of construction safety, the first attempt to use agent-based modelling was done by [17].

2. MATERIALS AND METHODS

A conceptual model was prepared. The conceptual model is focused around two main concepts. The first is the cognitive process of construction workers' safety behavior adopted from [18], and the second is the process of safety inspection using a UAS as described and tested by [14]. 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.

The construction site is characterized by the level of risk. 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 [19]. Reference [17] 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 behaviour 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 2500m2.

2.1. Cognitive Process of Workers' Safety Behavior

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 behaviour will be determined through the portrayed cognitive process in the model. All the equations in this section are adopted from [20]. The actual risk on site is perceived differently between one worker and another based on the perceiving coefficient [7]. 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. Therefore, the choice of safe or unsafe behaviour will be based on the below Equations 1 & 2 in the model:

if RA < PR, the worker will behave safely, (1)
but if RA > PR, the worker will behave unsafely, (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 location and the risk perceiving coefficient of the worker, such that:

$$PR = RP_{coef} \times AR \tag{3}$$

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

The risk perceiving coefficient is affected by the worker's previous experience, knowledge about risk and safety, as well as his risk attitude [21]. Risk attitude shows the affinity of the worker towards taking risk. The attitude of the worker will change if this worker undergoes a near miss or an accident. In such a case, the worker will become more risk averse. Conversely, the attitude of the worker will become more risk-seeking in the cases when the worker behaves unsafely but is neither warned by management 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 [11]. The risk perceiving coefficient will change based on the change of the attitude.

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 co-workers, representing the workgroup norm, and the drone, representing the management norm [18]. Hence, the risk acceptance is calculated based on Equation 5:

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

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. 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 [18]. Workers with stronger identification with the project 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 [18]. Both findings are reflected in Equation 5.

The workgroup norm is the worker's perception of the acceptable risk of his co-workers taking into consideration the amount of info that he can retain based on his memory. In the model, the worker can only observe co-workers close to him. While working, the worker observes his co-workers and updates his perceived workgroup norm by taking into consideration the average of the co-workers' risk acceptance as perceived by him according to Equation 6:

$$WN_i = \left(1 - \frac{1}{m}\right) WN_i^{prev} + \frac{1}{m}\left(\frac{1}{k}\sum_{0}^{k} PRA^n\right) \tag{6}$$

where m = memory capacity, k = total number of co-workers close to the worker i, and PRA^n is the risk acceptance of co-worker n as perceived by the worker i.

The management norm is the worker's perception of the acceptable risk by management in the project. The worker updates his perceived management norm according to Equation 7.

$$N_i = \left(1 - \frac{1}{m}\right) MN_i^{prev} + \frac{1}{m} PMA \tag{7}$$

where PMA is the management risk acceptance as perceived by the worker.

2.2. Safety Inspection by a Safety Inspector

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. 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.

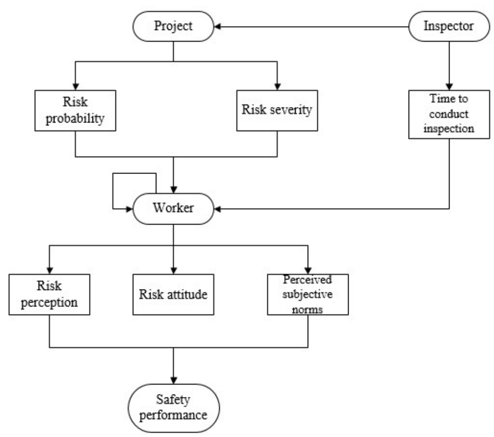

Figure 1 – Conceptual Framework: Safety Officer

To find the average time needed for the safety inspection of a typical 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. As for the frequency of inspections conducted in a day, 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 [22], 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.

2.3. Safety Inspection by an Unmanned Aerial System

A UAS consisting of one 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. Figure 2 summarizes the conceptual framework when a UAS is employed for safety inspection.

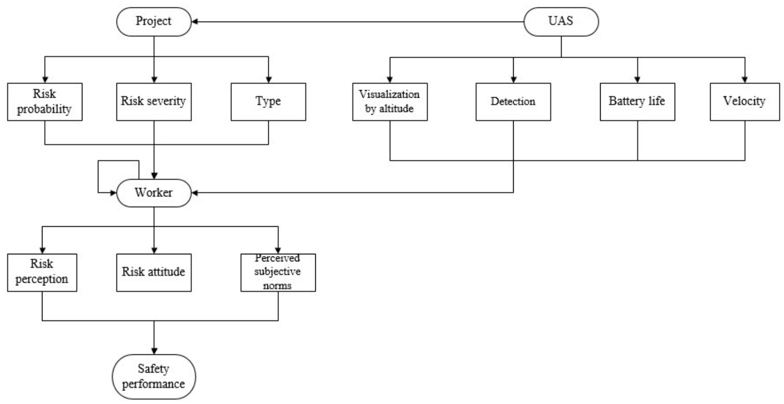

Figure 2 – Conceptual Framework: UAS

In order to have an efficient inspection mission, [14] 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 is created such that all the site area is covered by the drone flight at each level. The drone will move a certain distance then stop for a certain duration to capture photos and videos and then moves again repeating this process until the whole site area is covered. 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.

Based on the study by [14], only a certain percentage of requirements will be visualized at each level. Figure 3 shows the percentage of safety inspection requirements visualized at each level for two projects: A (horizontal-type) and B (vertical-type). 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.

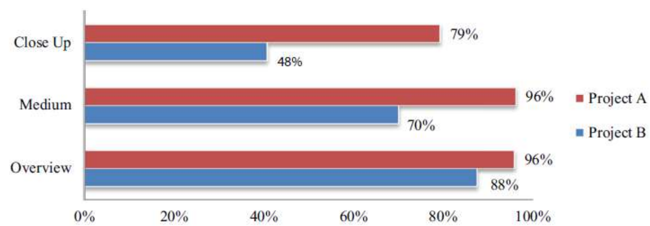

Figure 3 – Percentage of safety inspection requirements visualized by snapshots [13]

The photos and videos that are taken by the camera are scanned for detection through a certain algorithm and again only certain percentage of requirements will be detected based on the precision of the algorithm. The mechanism for detection along with its performance are adopted from the study by [23]. This algorithm can detect 86% of instances in outdoor near range visual assets and 84% in outdoor far range visual assets. 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.

The calculation of the footprint of the camera depends on the characteristics of the used camera as well as the height at which the camera is operating from the ground. The drone is assumed to follow a flat flying motion and the dimensions of the footprint, as shown in Figure 4 are calculated using the methods and equations from the study by [24].

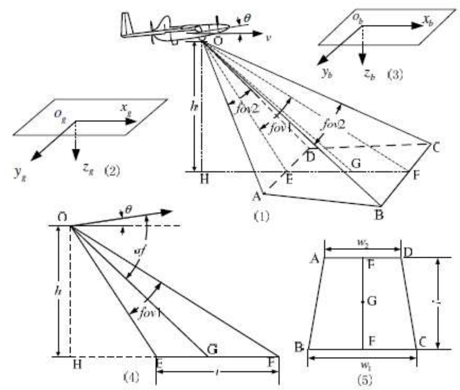

Figure 4 – The camera footprint in flat flying motion [22]

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 near empty. Manufacturers usually advise that the drone returns when the battery charging level reaches 30% [25]. This inspection by the drone can easily be repeated as much as needed per day since no physical effort will be required and since the safety of any personnel is not compromised. A timeout is set between inspections to take into consideration the possible need for battery replacement.

Based on the above-described processes, when an unsafe condition is encountered by the inspector of the UAS, the concerned party will be informed by management to resolve the problem. Moreover, when unsafe behavior by a worker is detected, the worker will be warned through direct communication.

3. RESULTS AND DISCUSSION

The conceptual model is translated into a simulation model and the safety indicators calculated.

3.1. Incident Rate

The first indicator used is a lagging indicator which is the incident rate. Equation 8 is used to calculate the incident rate and it is adopted from OSHA:

$$\text{Total Recordable Incident Rate} = \frac{\text{Number of recordable cases} * 200{,}000}{\text{Number of total labor hours worked in the year}} \tag{8}$$

To get reliable results, the model was run 100 times. Figure 5 shows the box plot for the incident rate for the 100 simulation runs. Box plot 1 is for the case of the safety inspector and 2 for the case of the UAS. The mean for the incident rate for the case of the safety inspector is 3.9. As for the case of the UAS, the mean is 0.63 which is much less than the previous case.

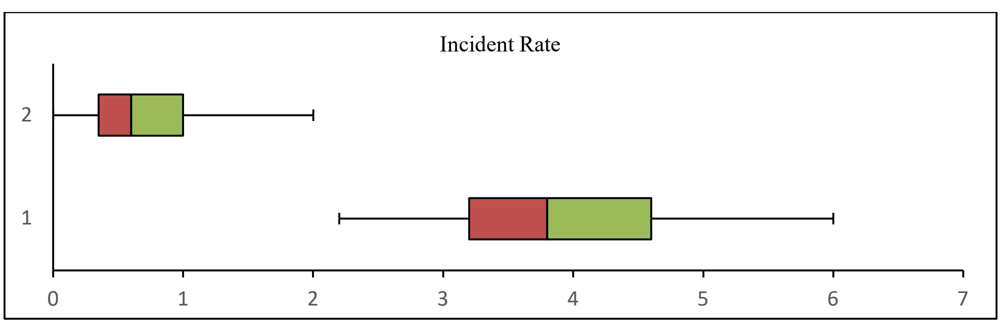

Figure 5 – Box plots for the incident rate of 100 simulation runs

3.2. Safety Behavior

The second indicator is the safety behavior of workers which is a leading indicator. The safety behavior of workers is examined 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 9 [26]:

$$\text{Unsafe Behavior} = \left(\frac{\text{Total observed unsafe behavior}}{\text{Total observed safe behaviour+Total observed unsafe behavior}}\right) * 100 \tag{9}$$

Figure 6 shows the change in the unsafe behavior ratio with time. The horizontal axis represents the time in hours in the simulation, bearing in mind that each 8 hours constitute one working day.

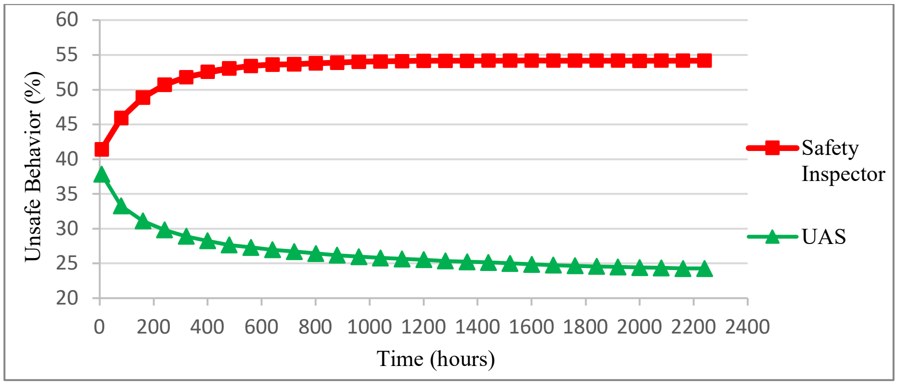

Figure 26 – The effect of intervention type on the safety behavior of workers

The results show that the unsafe behavior of workers increases with time in the case of the safety inspector. The model showed that for the given site area, 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 in the model 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, some of the unsafe behavior of the workers during these 3 hours can 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 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 decreases at a fast rate in the beginning and then this rate decreases gradually until the curve levels out towards a minimum value at around 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 7.

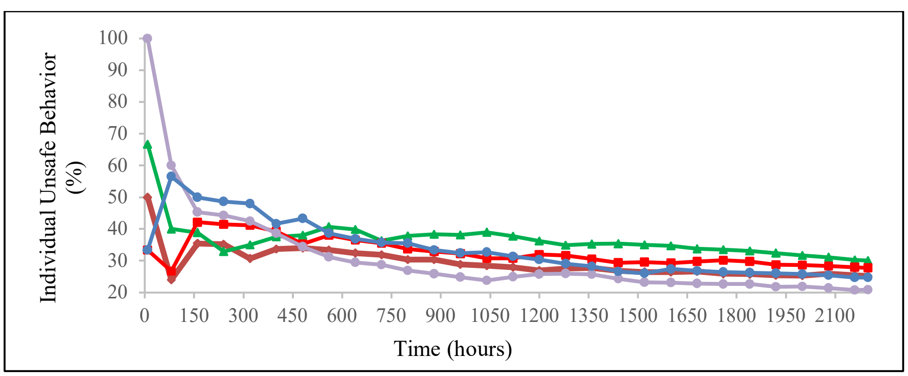

Figure 2 – Change of the individual safety behavior of workers

The curves 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 affects the rate of decrease of unsafe behavior.

3.3. 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 10.

$$\text{Hazards Reported} = \left(\frac{\text{Total hazards detected}}{\text{Total number of hazards}}\right) * 100 \quad (10)$$

Figure 8 shows the box plot for the % of hazards detected in 100 simulation runs. Box plot 1 is for the case of the safety inspector and 2 for the case of the UAS. 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.

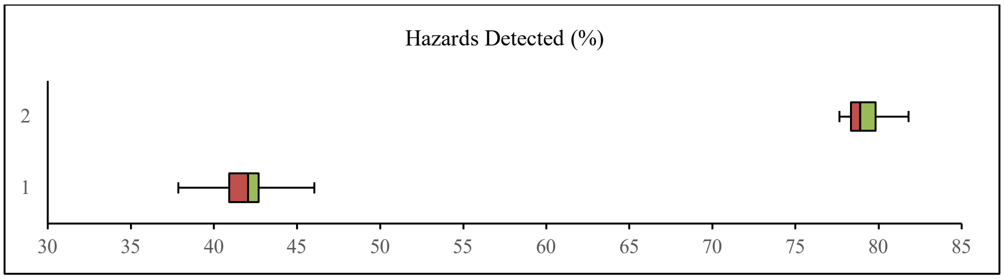

Figure 8 – Box plot for the % of hazards detected of 100 simulation runs

For the case of the UAS, the mean is 79,07%. The fact that the percentage of unsafe conditions detected by the UAS is high despite the restrictions imposed (visualization & detection by algorithm) is highly related to the frequency of inspections. The model showed that for the given site area, 8 missions in one day where able to be conducted. 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 another mission before the condition actually changes. This is to some extent a true reflection of reality 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.

4. CONCLUSION

An agent-based modelling tool was established to compare the development of the safety performance of a construction site when using an unmanned aerial system for safety inspection versus the traditional practice of a site inspector. The results showed better performance with the UAS. However, including UAVs in the safety management system must be accompanied with a set of standardized procedures for adequately planning the flight mission, collecting and storing the data, analysing this data, and taking the appropriate immediate and future managerial actions accordingly. Regarding the limitations of the study, 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, safety inspectors tend to take shortcuts to reach the locations where construction activities are taking place instead of 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 the model to further validate the model. Furthermore, it would be interesting to back up the study with cost analysis comparison.

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