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AGENT BASED SIMULATION OF WORKERS' BEHAVIOURS AROUND HAZARD AREAS IN MANUFACTURING SITES

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ABSTRACT

Rewards for risk taking behaviour by workers (if accidents do not occur) can be realised in the form of increased productivity or worker idle time. However, frequent unsafe behaviours of workers inevitably results in accidents and an associated loss in productivity. Workers' behaviour towards safety is influenced by management, who can encourage or discourage risk taking behaviour. In this paper, we explore the relationship between the perceived reward by individual workers who expose themselves to hazards and a management response in the form of inspections to monitor and address inappropriate behaviours. We conduct this study by developing an Agent Based Simulation Model, where workers are required to learn paths within a factory exposed to hazardous areas, with inspectors randomly moving around the factory to correct inappropriate behaviour if noticed. We assume workers are maximising their anticipated reward as they learn routes through the factory. This agent based model is used to explore the impact of inspection frequency and reward perception (i.e. parameters which can be influenced by management) on the number of workplace accident. The results demonstrated that the proposed model is a valuable tool to assist the management in predicting the potential safety improvement from safety management practices focusing on safety inspections, and changing workers perceptions.

Keywords:

Safety, behaviour, agent based model, accidents, hazardous areas, rewards, safety inspections

1 INTRODUCTION

Hazards can exist in almost every workplace and despite continuous efforts to mitigate risks and improve the safety, the rate of accidents and injuries still very high in many industries. Indeed, occupational safety organization around the world report alarming trends in workplace safety, for example: in the UK, the Health and Safety Executive (HSE) is the government organization responsible for regulating the development and implementation of safety rules. The HSE collects information on workplace accidents through the Reporting of Injuries, Diseases and Dangerous Occurrences Regulations, 2013 (RIDDOR). The manufacturing sector's non-fatal injury data provided by RIDDOR between 2016/17 and 2020/21 show that 32.6% of injuries have been caused by slips, trips and falls that can occur during movement. Safety violations have been widely recognized as the central cause of injuries and accidents. Hence, in order to improve safety in workplaces, there is ongoing interest in reducing the number of safety violations.

Safety violations can be present in different forms, such as the failure to wear protecting equipment (PPE), or taking shortcuts by travelling paths in the workplace where they are exposed to hazards as opposed to less hazardous paths in compliance with company guidance. In this study, we focus on the latter, by evaluating how the engagement of workers in shortcuts can impact the safety and productivity. Taking shortcuts is an intentional act, but non-malevolent. Indeed, workers expose themselves to hazards to save time, but they do not intend to cause damage to the organization.

Workers are often exposed to contradictory pressures, when for example, they have to balance production pressure with the need for safety. Such conflict may result in behaviour, where the workers start "cutting corners" to boost output. However, aggressive attitudes in the workplace can co-exist with risk avoidance behaviour when for example safety inspectors are around.

In this study, we investigate the impact of safety inspections on workers' accidents through changing behaviour. To model the safety-related behaviour, we introduce an Agent Based Simulation approach to: 1) Model how the workers learn about their environment, to determine their autonomous movement paths to save time, 2) simulate the aggressive behaviour of workers around hazardous areas, and study the consequent potential injuries, 3) Simulate the changes in workers behaviour from being aggressive to avoiding cutting corners when the safety inspector is around, 4) evaluate the impact of safety inspections, and rewards perceptions on the safety behaviour, to help the organization setting an efficient safety management policy.

The rest of the paper is organized as follows: Section 2 describes the academic background and related works, section 3 explains the research methodology adopted, section 4 describes the Q-learning algorithm, the proposed Agent Based Simulation framework is presented in section 5, the simulation results are detailed in section 6, and we end up with concluding remarks and some future works.

2 BACKGROUND AND LITERATURE REVIEW

2.1 Agent Based Modelling and Simulation

Agent Based Modelling and Simulation (ABMS) can be defined as a simulation system with agents that repeatedly interact with each other and with their environment in an autonomous way (Parker (2019) ; El Raoui, Oudani, and Alaoui (2018)). The agents in ABMS have certain properties and attributes (Wooldridge and Jennings (1994) ; El Raoui, Oudani, and Alaoui (2020)): autonomous, proactive, interacting, and unique. These properties enable the agent to communicate with other agents, interact with the environment, and make decisions in response.

2.2 Agent Based Modelling for safety behaviour

A wide range of simulation techniques have been used in previous studies to understand and address issues related to safety. Agent based modelling has gained a lot of interest in modelling safety-related behaviours. It was found that agent based modelling surpass the discrete event simulation at micro-level details of modelling, such as the behavioural aspects. Owing to the ability of ABM to capture the interactions between agents.

ABM have been mostly used to study safety behaviours in the construction industry. Lu, Cheung, Li, and Hsu (2016) proposed an ABM to investigate the impact of the different interactions between workers, and the various safety investment on improving the safety on site. In order to investigate ways to limit the risky behaviours of construction workers, Choi and Lee (2018) proposed a socio-cognitive approach based on ABM to simulate the social influence. Taillandier and Taillandier (2014) developed an ABM to access the impact of potential risks and work accidents on the costs and quality of work. ABM was also combined with System Dynamic (SD) in several recent studies, for a more comprehensive analysis of safety behaviour aspects. A SD-ABM simulation model was developed by Nasirzadeh, Khanzadi, and Mir (2018) to examine the impact of social contagion on the violation of safety rules.

Manufacturing is different from construction, and to the best of the authors' knowledge, no existent study has modelled the worker's aggressive behaviour around hazardous areas in manufacturing sites, its impact on the accidents rate and productivity loss, and how the safety inspection can reduce rate of injuries by pushing workers to avoid risk taking behaviour.

3 RESEARCH METHODOLOGY

This paper aims to assess the manufacturing site's safety by considering the workers safety violations around hazardous areas. Introducing safety inspections, and changing worker's valuation of risk taking can play an essential role in reducing the violations, which we try to demonstrate in this paper. The methodology used is as follows:

- Design the learning process of agents, to represent how the workers determine their movement paths on site.
- Define the behavioural rules of agents, and integrate it with the learning step to build the agent based simulation model.
- Define the scenarios to be simulated, and run the model to analyse the potential consequences of workers' behaviour on productivity and safety.
- Analyse the results and identify potential interventions by the organization to improve the safety.

4 Q-LEARNING BASED PATH DETERMINATION

When training an agent, different types of learning can be used such as supervised, and unsupervised learning, and reinforcement learning. The latter is used in this study. Reinforcement learning, can be defined according to Gatti (2015), as a machine learning technique that describes how a set of subsequent decisions will lead to the accomplishment of a goal, which is considered as a trial and error process to learn patterns.

Q-learning algorithm is a model free reinforcement learning algorithms used to train agents to find the optimal action in a Markovian Decision Process Dayan and Watkins (1992).The fundamental idea of Q-learning is that the agent learns an action value function to maximize the total rewards received from the environment. Considering that S is the set of possible states of an agent within an environment, and A the set of possible actions that the agent can choose from. The state, action, and reward of agent i at time t can be represented as:

$$s_t^i \in S, a_t^i \in A, r_t^i \in S \times A \rightarrow \mathbb{R} \tag{1}$$

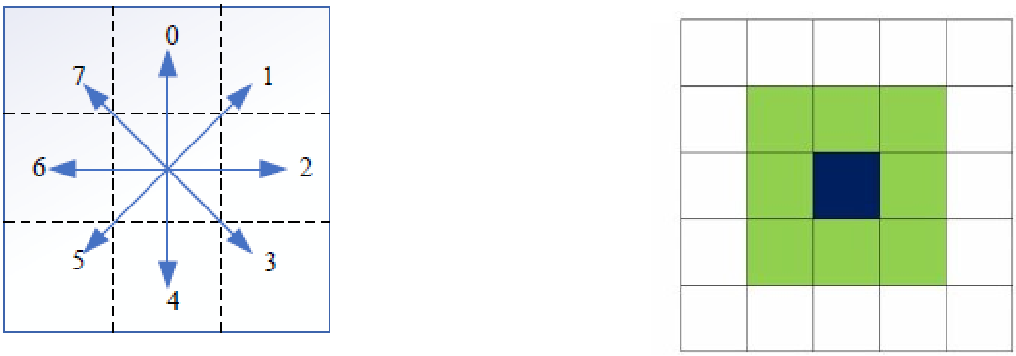
The Q-Value can be updated as follows:

$$Q(s_t, a_t) = (1-\alpha)Q(s_t, a_t) + \alpha\left[r_{t+1} + \gamma \max Q(s_{t+1}, a_t)\right] \tag{2}$$

where α is the learning rate, and γ is the discount factor. We put, $\alpha = 1$ which assumes that the new value does not take into account the previous values of Q. We consider $\gamma = 0.8$ as it's usually set to in previous studies Samma, Lim, and Saleh (2016) which will make the agent strive for a long-term high reward.

The Q-learning algorithm is integrated in the proposed simulation model, to simulate how the agents learn about the environment to determine the best path to reach storage sites. The states of each agent are the possible neighbourhoods. In this paper, we use the Moore neighbourhood topology (i.e. a two-dimensional square lattice that contains a central cell surrounded by eight adjacent cells) Moore (1964). Changing from a neighbourhood (i.e. cell) to another is the action, therefore, 8 basic actions are available to each agent as shown in Figure 1a.

The goal of our agents is to reach the destination as fast as possible, therefore the designed reward is a function of the distance to the target point. Let $d(o,T)$ be the distance between the neighbour O



(a) (b)

Figure 1: (a) The agent's actions, (b) Moore neighbourhood

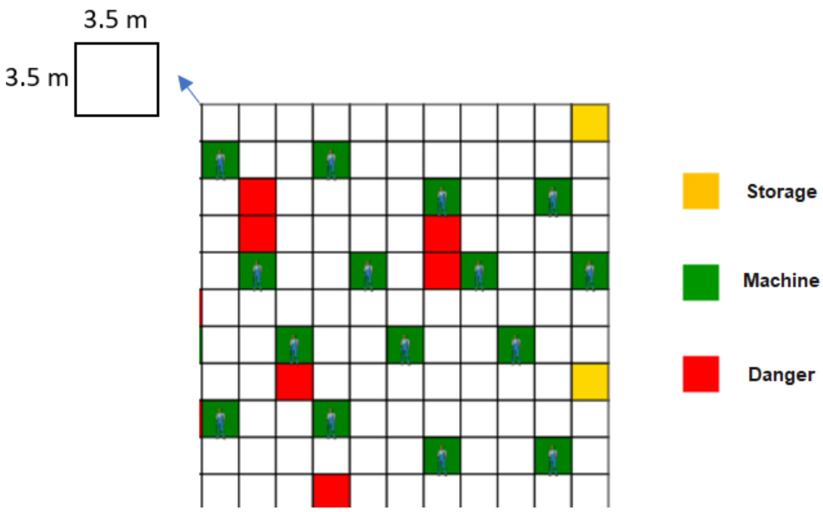


Figure 2: The virtual working environment.

and the target point T. The reward is computed as follows:

$$r = \begin{cases} 1, o = T \\ \frac{1}{d(o,T)}, \qquad o \neq T \end{cases} \tag{3}$$

5 ABMS FRAMEWORK

5.1 The virtual working environment

In agent based models, an agent can interact with other agents, and the environment. These interactions are represented in the model space where the agents can move. Different topologies can be used to model the space Macal and North (2009). In this study, we use a discrete spatial topology to represent the workplace. As shown is Figure 2 , the virtual manufacturing site consists of a grid layout of 400 cells characterized by their location (x,y) coordinates, and an attribute to characterize the type of each cell. This attribute is represented in the model by a variable that can assume the following values:

- Normal: cells with no manufacturing activities. At the beginning of the model, all agents cells are generated as normal one.
- Machine: cell that represent the work station.
- Danger: cells with hazardous conditions, placed randomly on the site.
- Storage: cells to represent the storage sites.

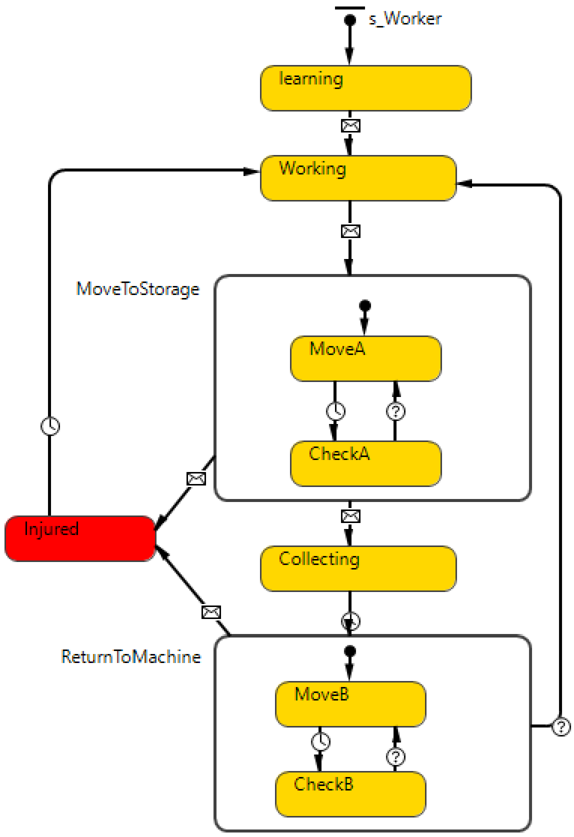


Figure 3: Workers' state chart.

The agents move from cell to cell on the grid, and the cells immediately surrounding an agent are its neighbourhood. Two kinds of cell neighbourhood are usually considered: i) the von Neumann's and ii) the Moore's (Figure 1b). The latter is considered in this work.

5.2 The agent's behavioural rules

5.2.1 Workers

Workers are the main agents in our model. They are required to move from work stations to the storage sites to pick items, or to store semi-finished products. Accidents and injuries can occur with a certain probability during movements if a worker is in a danger zone. To describe their behaviour, we use the state chart in Figure 3. The first step in our model, before the agents start working is the learning phase. In the learning process, we replicate how the workers learn about the environment, to find the best path between two workplaces using a path determination mechanism, based on the Q-learning algorithm. We assume that the workers have an aggressive behaviour, so they choose shorter, riskier paths to reach the storage sites. However, worker's aggressive behaviour can change if the safety inspector is around. Indeed, workers will tend to avoid stepping on a danger zone to prevent being penalized by the inspector.

5.2.2 Safety Inspector

The inspector roams the site to make safety checkup, moving from one cell to another with a given frequency per day. The inspection aims to discourage undesirable behaviours and increase safety compliance by making the agent avoid danger zones.

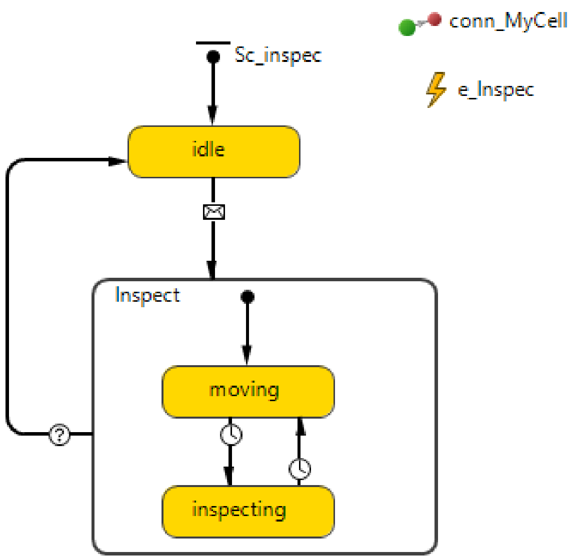


Figure 4: Safety Inspectors' state chart.

6 SIMULATION AND ANALYSIS

The proposed ABM was implemented using the Anylogic software. This study is based on a hypothetical case. We consider a manufacturing site of, 4900 m², with 50 work stations, 50 workers, and 3 storage sites. The site involve 20 danger zones, where each zone occupies 12.25 m².

The model simulates the movement of workers from working to storage stations with a certain frequency. The inputs to our model are the following:

- The frequency of movements: controlled through an event generated following a uniform distribution, uniform (2h,3h).The event create a collection order from a random storage site.
- The probability of accidents in danger zones is set to 0.2
- The average walking speed of workers is 1.8 km/h.
- The frequency of inspection was set based on each particular scenario simulated to represent the different management policies.
- The duration of injuries is set to 1 day.

The user interface is shown in Figure 5 that gives control to the steps of the simulation, and provide a visualization of the statistics about the accidents. At the start of the simulation, the agents are trained to find their paths to each of the storages by performing 100 learning-passes. Once the learning process is complete, the user can launch the work process.

The purpose of the model is to assess the relationship between the rate of injuries, perceived rewards for risk taking by workers and managerial inspection policy.

6.1 Scenario 1: Avoider vs Aggressive

In this scenario, we simulate the aggressive and avoider behaviour of agents while moving around the site during 8 hours of work. The purpose is to quantify the potential savings in time from taking shortcuts.

The results in figure 6 shows that aggressive workers can effectively save time while moving to any of the storage sites. The amount of time that can be saved depend on the worker's placement, the destination, and the number of danger zones included in the best path of the worker.

The mean time that can be saved by the workers to storage 1,2,3 is respectively 7.4, 9 and 7.8 minutes. The lower whiskers represent the workers with slight time saving, that can be explained by their proximity to the storage sites, or either their safe fast path, means that they don't need to walk through danger zones to reach the storage. The upper whiskers represent the workers who can gain interesting saving by being aggressive, that could range between 12 and 22 min for storage 1, 12 to 21

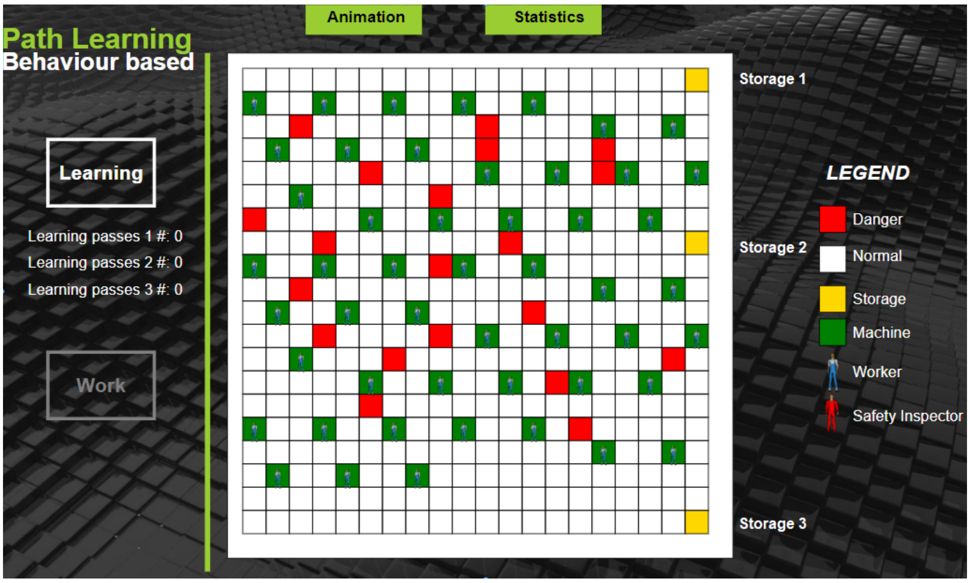


Figure 5: The customized user interface.

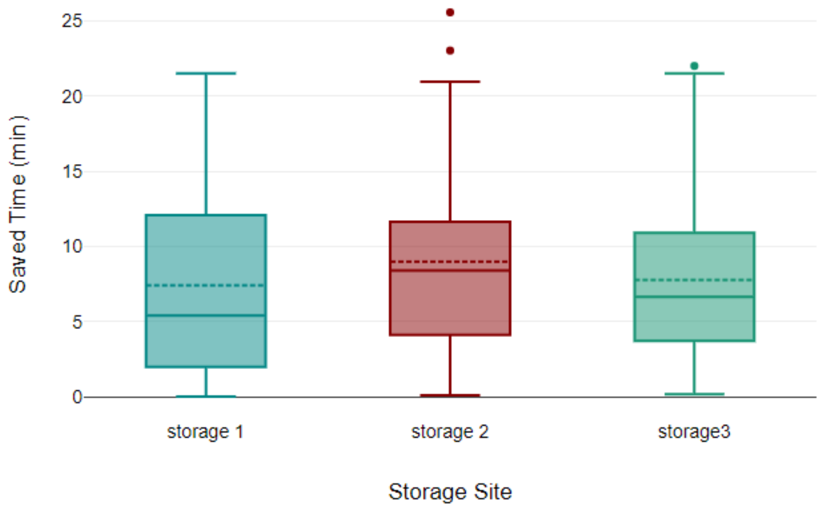


Figure 6: Travel time saved by aggressive workers to each storage site during 1 day work.

min for storage 2, and 11 to 19 min for storage 3. We observe some outliers in storage 2 and 3 which represent the workers who have greater interest in making shortcuts. The provided results about the potential savings can give insight on the possible gain in productivity, and also helps in identifying the workers that are more likely to take shortcuts.

6.2 Scenario 2: Safety inspection

This scenario examined the impact of different safety inspection policies on the worker's safety behaviour, and the potential improvement in safety. During an inspection, an inspector is simulated walking through the entire workplace so that they cover it twice in 2 hours. We perform 10 simulation runs of 1000 hours and report the number of accidents. Five inspections policies were considered with different frequencies, starting an inspection every 2, 3, 4, 5 or 6 hours. We first simulate the case without inspection to serve as a reference point for comparison.

The results shown in Figure 7 demonstrate the role of safety inspection in reducing the rate of injuries. Unsurprisingly, We see that the mean number of accidents is decreasing as inspections increase. Introducing the most frequent level of inspections lowered the accidents by 23%. In terms of productivity, the duration of injuries is reduced by 96 hours which would improve productivity. However, inspections

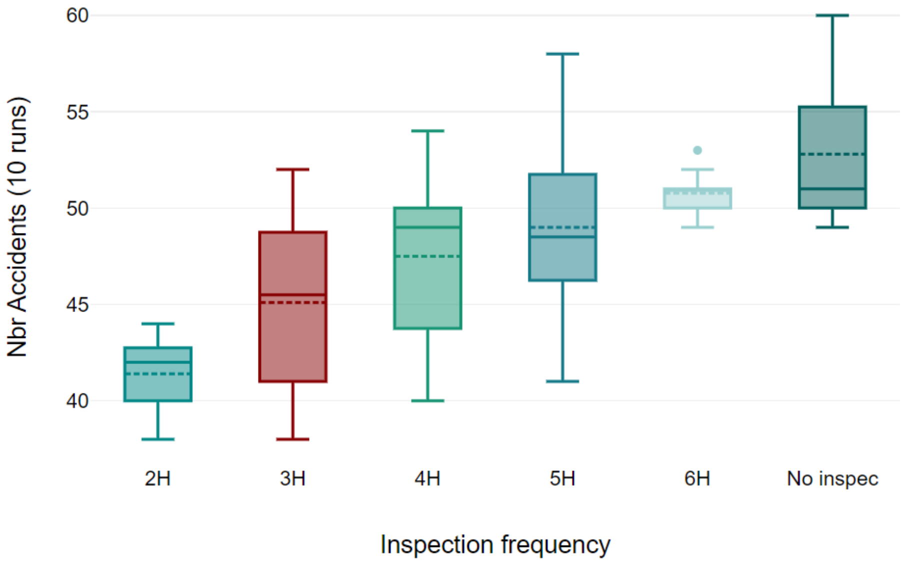


Figure 7: Accidents statistics for each inspection frequency.

would require an inspector working all the time and the optimal solution may be with a more moderate inspection policy.

6.3 Scenario 3: Perceived risk-taking reward

An alternative influential factor in worker risk taking behaviour is their perceived reward for exposure to hazard. Changing such perceptions provides an alternative route to improving safety in the workplace. The purpose of this scenario, is to examine the impact of diminishing the expected benefits on risk-taking behaviour, by applying a discount factor on the perceived reward.

Let ϕ be the discount factor. The perceived reward from using a hazard zone is:

$$r = (\frac{1}{d(o,T)})\phi \tag{4}$$

We run the experiments for 3 reward profiles corresponding to a discount of 25%, 50%, and 75% to correspond to Low, Moderate and High perceived reward for risk taking. Ten simulation runs of 1000 hours were performed for each combination of risk perception type and inspection policy. The mean number of the potential accidents are shown in Figure 8.

We see under all three risk perception types the higher the frequency of inspection the lower the accident rate. However, the impact of inspections is slight for low and moderate reward types but substantial for high. As such, depending on the characteristics of the work force, inspector may be adding little value. In fact, changing the characteristics of the workforce to move from high reward to moderate or low may be a more laudable goal, as a maximum inspection policy for a high reward workplace would have the same frequency of accidents as a moderate reward workplace with no inspections.

While the inspections can be very costly, changing people's perception can be extremely tricky. Therefore, management need to find the right balance between cost and complexity when implementing safety management practices. The proposed model can assist the management in predicting the potential safety improvement from each strategy profile.

7 CONCLUSIONS AND DISCUSSION

This research proposes an Agent Based Simulation framework to understand the workers' behaviour towards safety when moving around hazardous areas and evaluate the impact of different inspection policies on reducing the accidents rate. The proposed model was developed with three objectives:(1) Simulate the learning process of agents to determine their autonomous movement paths, based on the

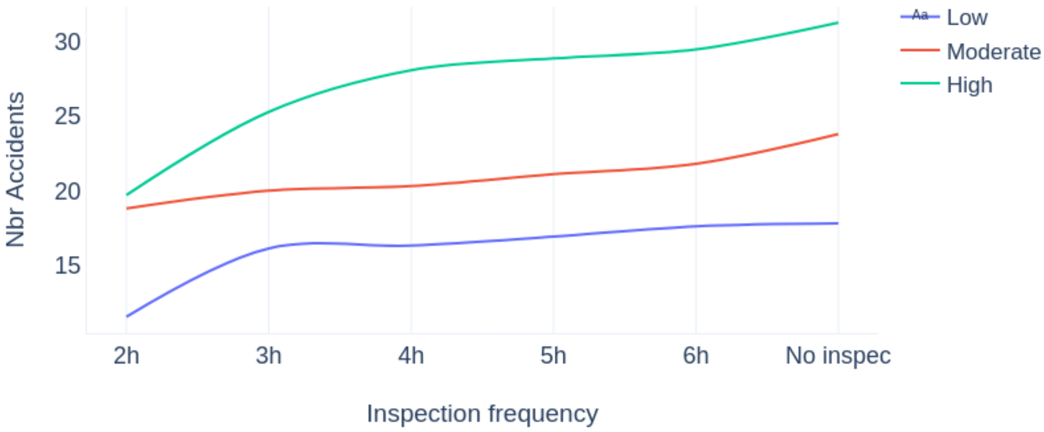


Figure 8: Accidents statistics for each inspection frequency, reward profile.

Q-learning algorithm. (2) model the different behaviours the workers can have towards safety. (3) quantify the potential injuries and productivity loss under different safety management practices.

The proposed model was demonstrated to work effectively through a hypothetical case study. Several scenarios were tested to analyse and asses the impact of the workers'aggressive behaviour on the productivity and safety. The results show that the model is potentially a valuable tool to help organisations understand the impact of risky behaviour and identify the potential ways to improve the safety.

- The potential time saving from taking shortcuts gives insights about the workers that are more likely to violate the safety rules.
- The model can help to predict the potential injuries and productivity loss arising from an aggressive attitude.
- The model can assist the management in determining the effectiveness of the safety inspection practices, focusing on the safety inspections and rewards perceptions, on improving the safety.

Social interactions with the co-workers can influence the safety rules compliance due to the social pressure and the social learning. As future work, the proposed learning process can be improved by integrating the social learning element to the reward design. The integration of the social component can assist the organisations to better understand the emergent behaviours, and design the appropriate strategies to mitigate the risk. The extended version of the model will be applied to a real case study. We are currently collecting the data on workers movement and their environment from a workshop in the University of Edinburgh.

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