**A Probabilistic Approach to Dynamic Hazard Zone Mapping in Highway Work Zones**

# **Introduction**

Highway work zones are inherently complex and hazardous environments where the safety of construction workers and motorists is constantly challenged by active construction and traffic flows. The increased number of accidents and fatalities associated with these zones has led researchers to focus on developing more effective safety measures (Karr, 1998; Venugopal & Tarko, 2000). Accidents in these areas can result from a variety of causes including, but not limited to, vehicular collisions, worker and equipment interactions, and the improper management of traffic flow.

One of the critical issues within these zones is the prevention of near-miss incidents and collisions between construction equipment and onsite workers. The effectiveness of hazard zone mapping plays a pivotal role in this context, serving as a crucial mechanism for incident detection. Traditional approaches to hazard zone mapping typically employ static models, which use simple geometric shapes, such as circles, to define areas of danger around construction equipment. However, these static models are often insufficient for accurately representing the complex, dynamic interactions that occur between mobile workers and equipment in a changing work environment. As a result, they may fail to provide timely alerts or appropriate spatial coverage, leaving workers inadequately protected from potential hazards (Bai et al., 2010; Elias & Herbsman, 2000).

In highway work zones, the reliance on simple static circular hazard zones is problematic, particularly in congested environments. One significant issue is the occurrence of false alarms when individuals positioned laterally to a vehicle, in what would typically be considered a safer area, are still alerted by the hazard zone system. Moreover, the size of these hazard zones does not adjust dynamically according to the vehicle's speed. At high speeds, safety necessitates wider zones, while at lower speeds, the zones should contract to prevent unnecessary alarms for individuals who are farther away yet still safe. Furthermore, current practices usually define danger around vehicles using one or two circular zones to indicate different levels of hazard and warning. However, these models fail to represent the gradient of hazard probability extending outward from the equipment. This lack of probabilistic differentiation can result in either overly cautious or insufficiently prepared responses to actual dangers at various distances from the equipment (Kuennen, 2007; Rashid et al., 2019).

The primary objective of this study is to develop a probabilistic, dynamic hazard zone mapping model that adjusts in real-time to the changing conditions within highway work zones, thereby enhancing the responsiveness and effectiveness of safety measures.

# **Literature Review**

## **Review of Hazard Zone Mapping Methods**

Hazard zone mapping in construction and industrial environments traditionally relies on static models that typically utilize simple geometric shapes, such as circles, to demarcate areas of varying danger levels around construction equipment. These models often designate a warning zone and a more critical hazard zone, reflecting different levels of proximity and associated risk. Despite their widespread adoption, these static models are noted for their limitations in accurately capturing the dynamic interactions that occur on site, which can lead to inefficiencies and potential safety oversights (Abotaleb et al., 2016).

Hazard zone mapping methodologies have evolved significantly to address the dynamic and complex nature of construction and industrial environments. Automated and real-time data-driven approaches are becoming increasingly crucial for ensuring worker safety amidst the interplay of heavy machinery and human activities. A notable advancement is the use of automated classification systems that employ real-time location systems (RTLS) for crowd-sourced data collection. This method transforms worker location tracks into grid density maps, which dynamically illustrate hazardous and safe areas, significantly improving hazard awareness and site management (Li et al., 2017).

The integration of Geographic Information Systems (GIS) and semantic enrichment techniques further enhances the precision and effectiveness of hazard mapping. GIS allows for detailed mapping of site layouts and the assessment of dynamic safety measures, while semantic enrichment of spatio-temporal data provides deeper contextual insights into worker movements and potential risks (Arslan et al., 2019; Sarasanty, 2020). Moreover, proximity zone design around heavy equipment, based on construction resource tracking data, has shown to effectively mitigate risks by creating validated hazard zones that increase spatial awareness and prevent accidents (Awolusi & Marks, 2019).

Emerging technologies such as machine learning and computer vision are also being utilized to predict and analyze interactions between workers and machinery, thereby identifying and mitigating safety hazards more effectively. These systems analyze the spatial-temporal relationships and trajectories of workers and equipment to pinpoint danger zones and generate timely safety alerts, contributing significantly to the reduction of accidents and enhancement of overall safety on construction sites (M. Wang et al., 2019). Each of these technological advancements demonstrates a shift towards more dynamic, integrated, and data-driven safety management practices that cater to the unique needs of modern industrial and construction settings.

## **Shortcomings in Existing Hazard Zoning Methods**

Static and circular hazard models, traditionally used in construction and industrial environments to delineate safety zones, are based on simple, predefined geometries such as circles that mark hazardous and warning zones. However, these models suffer from significant limitations, primarily their inability to adapt to changes in the environment and operational conditions. Because they do not account for the dynamic interactions between mobile workers and machinery, these static models often fail to provide accurate and timely updates that reflect the current state of the work area. This leads to a mismatch between the actual and perceived risks, potentially causing safety systems to either overreact or underreact to threats (Li et al., 2016). Additionally, the circular model assumes uniform risk in all directions from the center point, which is rarely accurate on a construction site. This geometric simplification ignores the directional nature of many hazards, such as those posed by specific machinery movements or operational directions, leading to areas being incorrectly labeled as safe or dangerous (Luo et al., 2016).

Moreover, the rigidity of static models means they cannot easily incorporate real-time data, such as the actual movements of workers and equipment, which are crucial for accurate hazard assessment. This limitation significantly reduces their utility in environments where conditions change rapidly, and where the timing and location of potential hazards can vary significantly over the course of a day or even within hours. The need for a more adaptive and accurate hazard mapping approach is clear, as these traditional models do not provide the flexibility or the level of detail necessary to effectively manage the complex safety challenges present in modern construction and industrial sites (Umer et al., 2018).

## **Recent Technological Advances in Dynamic Mapping for Construction Safety**

Recent advancements in sensor technology and data analytics have significantly transformed the approach to dynamic mapping in construction environments, facilitating more accurate and real-time hazard detection and site management. These technologies harness the power of real-time data collection via various types of sensors, enabling a more responsive and adaptive safety management system.

One of the key developments is the integration of 3D imaging technologies, such as LiDAR, with real-time data processing algorithms to capture the dynamic nature of construction sites accurately. These methods allow for the rapid and precise planning of 3D imaging in dynamic environments, enhancing the capability to reduce spatial conflicts and improve construction quality (Zhang & Tang, 2015). Similarly, Wireless Sensor Networks (WSNs) have been increasingly utilized to monitor various environmental parameters in real-time, providing crucial data for dynamic mapping and structural health monitoring. This approach not only supports the safety management but also aligns with the Building Information Modeling (BIM) systems to facilitate a holistic view of construction site safety and operations (Kontaxis et al., 2022).

Another significant advancement is the use of Internet of Things (IoT) technologies in construction safety management. Systems integrating IoT with Building Information Modeling (BIM) have been developed to monitor the proximity of workers to dangerous areas or moving machinery in real-time. These systems employ Wireless Sensor Networks (WSNs) to detect when individuals enter predetermined proximity zones that signal high-risk areas, subsequently initiating automatic safety responses such as alerts. This capability not only enhances the efficiency of safety management but also provides a visual interface for monitoring the spatial distribution of safety hazards across the construction site, improving the overall management of worker safety and operational protocols (Cheung et al., 2018).

# **Methodology**

## **Model Development and Specifications**

The study aims to develop a probabilistic model that dynamically maps hazard zones around construction equipment within highway work zones. The hazard zones are represented using a bivariate Gaussian distribution, designed to adapt in real-time to the equipment's direction and speed. The directional change of probability is managed by varying the standard deviations of the distribution along both axes, aligning the major axis with the direction of movement. This alignment allows for an elongated hazard zone in front of the moving equipment, where the risk is highest. The speed dependency is addressed by expressing the standard deviation as a function of speed, ensuring that the hazard zone size appropriately reflects the equipment’s velocity.

## **Data Collection and Processing**

Data from GPS and IMU sensors will be utilized to obtain real-time location and movement information for both equipment and workers. GPS data will determine the center point of the Gaussian distribution, while IMU data will provide insights into the equipment’s speed and directional changes, crucial for adjusting the distribution’s parameters in real-time. This integration ensures that the hazard zones are accurately mapped and updated in accordance with the physical dynamics observed on the site.

## **Simulation and Testing**

**Simulation Strategy:** The primary objective of the simulation is to evaluate the effectiveness of the hazard zone mapping model for construction equipment within highway work zones. The simulation will be conducted using Webots, a robot simulation software, to replicate real-world scenarios. The strategy involves simulating equipment movements, detecting worker presence within the hazard zone, and evaluating the response and outcomes based on predefined criteria.

**Environment Setup:** A realistic highway work zone environment will be created in Webots, including static objects like barriers and road signs to replicate real-world conditions. Construction equipment and worker objects will be placed within this environment to simulate actual work zone scenarios.

**Random Speed and Worker Location Generation:** To simulate variability in equipment speeds, 50 random speeds will be generated within the range of 5 to 40 km/hr (taking the average and standard deviation as 20 km/h and 5km/h, respectively). Additionally, a grid of points representing potential worker locations will be established ahead of the equipment, with intervals of 1 meter. This grid will span 10 meters across the road and extend 5 meters along the road (Figure 1).

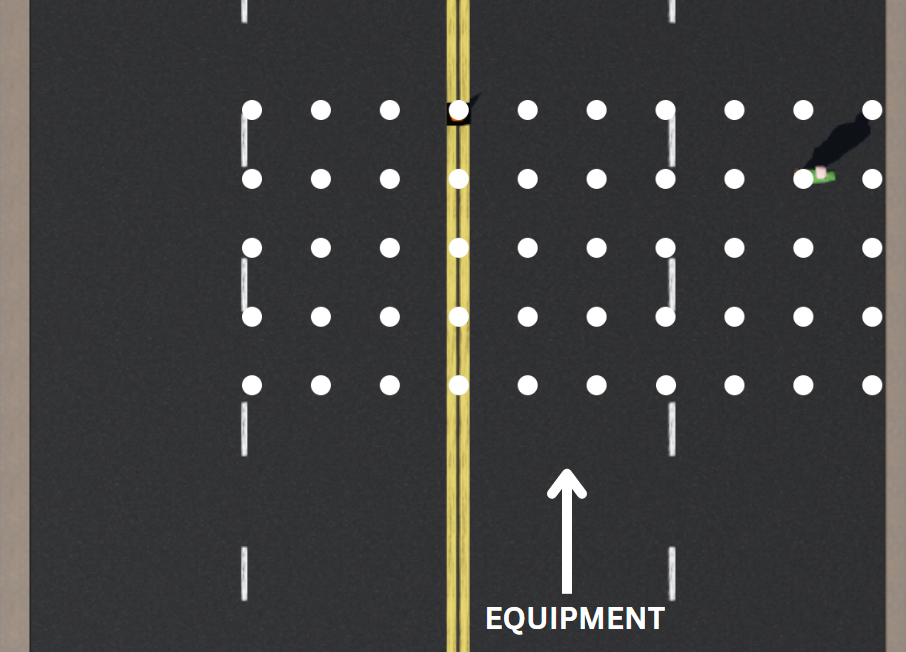


Figure 1. Grid points for worker locations

**Simulation Scenarios:** Two distinct scenarios will be simulated to comprehensively evaluate the hazard zone model.

Scenario 1: Equipment Moving Forward

In the first scenario, the equipment will move forward at one of the randomly generated speeds. When a worker enters the hazard zone, the equipment will continue at the same speed for 2.5 seconds, simulating the operator's reaction time. Following this, the equipment will decelerate at a rate of 1.9 m/s² until it stops. The distance between the equipment and the worker when the equipment stops will be measured. The outcomes of the simulation will be classified as follows:

* **False Negative:** The equipment hits the worker or comes within 1 meter before stopping.
* **True Positive:** The equipment stops with the worker 1 to 2 meters away.
* **False Positive:** The equipment stops with the worker more than 2 meters away.
* **True Negative:** No worker enters the hazard zone and no worker is within 2 meters.

Scenario 2: Equipment Turning

The second scenario will involve the equipment executing a turning maneuver at one of the randomly generated speeds. The same steps for detection, reaction, deceleration, distance measurement, and outcome classification will be followed as in the first scenario. This scenario will test the model's effectiveness under more complex movement conditions.

**Data Collection and Analysis:** Data will be collected for each simulation run, including the speed of the equipment, worker location, distance to the worker when the equipment stops, and the result classification. This data will be analyzed to evaluate the effectiveness of the hazard zone model under various conditions.

## **Field Experimentation**

Following successful simulations, a field experiment will be conducted to test the model under actual working conditions. Equipment will be fitted with the necessary sensors, and data will be collected during typical operations within a controlled section of a highway work zone. This real-world testing is crucial for validating the model’s practical applicability and its ability to adaptively map hazard zones in a dynamic, unpredictable environment.

## **Analysis and Model Refinement**

Data collected from the field will be analyzed to evaluate the performance of the hazard mapping model. The focus will be on the model's accuracy in predicting and adapting to changes in hazard zones, its reliability in various operational conditions, and its practical utility in improving safety measures. Adjustments and refinements will be made based on this analysis to enhance the model's accuracy and functionality.

# **Results**

## **Theoretical Derivation of Hazard Zone**

The hazard zone mapping model proposed in this study is based on a probabilistic approach using a bivariate Gaussian distribution. The derivation of the hazard zone involves the following parameters:

1. **Center Point (𝜇𝑥, 𝜇𝑦​):** The center point of the hazard zone corresponds to the position of the construction equipment within the highway work zone.
2. **Standard Deviations (𝜎𝑥, 𝜎𝑦):** The standard deviations along the x and y axes determine the spread or width of the hazard zone in the respective directions. These standard deviations are functions of the equipment's speed and direction.

Expressions for 𝜎𝑥 and 𝜎𝑦 in terms of speed are initially determined based on theoretical hazard zone dimensions recommended in existing research, and then refined through a software simulation. A six-step procedure is recommended in a work by Shen et al., (2016) to draw hazard zones around various construction equipment. These procedures are used to come up with initial values for the coefficients. The procedure is detailed below:

1. **Equipment Footprint:** This parameter is the overall dimension of the equipment, which depends on the type of equipment. The equipment is assumed to have a length of 5 meters and a width of 2.5 meters for this analysis.
2. **Initial Safety Boundary:** The initial safety boundary is taken to be 2 meters around the equipment.
3. **Equipment Function:** This step involves determining the required safety distance based on the function and type of movement involved in the equipment. For example, the hazard zone of an excavator will have a circular shape with a radius governed by the size of the rotating arm. As the main focus of this study is on moving equipment such as wheel loaders and dump trucks, the hazard zone is governed by the speed of the equipment. This forms the basis for computing the distance required for the equipment to stop once a hazard is perceived by the operator, which is addressed in steps 4 and 5. Although this step considers the turning radius as an additional criterion in the original research, it is not considered in this study as the proposed hazard zone gets data in real-time and follows the equipment path dynamically.
4. **Operator Reaction Distance (RD):** The reaction distance is the distance covered by the equipment between the moment the operator perceives the hazard and takes measure. It is computed as:

where 𝑣 is the speed of the equipment in m/s, and 𝑡 is the reaction time. The reaction time 𝑡 is recommended to be 2.5 seconds (MUTCD, 2009; Shen et al., 2016; J. Wang & Razavi, 2016). Thus, the equation simplifies to:

1. **Braking Distance (BD):** The braking distance is the distance the equipment will travel between the moment the operator takes action and the equipment comes to a full stop. This distance is computed as (Shen et al., 2016; J. Wang & Razavi, 2016):

where 𝑣 is the speed of the equipment in m/s, and 𝑎 is the deceleration of the equipment in m/s², taken as 1.9 m/s² (J. Wang & Razavi, 2016) [0.7 another research, and around 1.4 from the simulation (this is taken)]. The braking distance could thus be expressed in terms of speed as:

1. **Determine Hazard Zone:** The final step involves determining the resulting hazard zone based on steps 1 through 5. In this study, the hazard zone is taken to be elliptical in shape, following the projection of a bivariate Gaussian distribution with the major axis representing the direction of movement of the equipment. The lengths of the major and minor axes of the ellipse are computed based on the values in the previous steps as follows:

* Major axis:
* Minor axis:

To determine 𝜎𝑥 and 𝜎y, these values are equated with the equation of the ellipse projection of the proposed bivariate Gaussian probabilistic plot. The hazard zone is assumed to represent the ellipse with a 70% probability of hazard.

For a bivariate Gaussian distribution, the equation of the ellipse representing the 70% probability contour is given by:



where k is a constant that corresponds to the 70% probability contour. For a 70% confidence level, the value of k is obtained from the chi-squared distribution table corresponding to the 30th percentile (i.e. the 70% hazard probability) for 2 degrees of freedom. This value is approximately 0.713.

The major and minor axes of the ellipse in terms of the standard deviations are:

* Major axis:
* Minor axis:

Equating these with the calculated dimensions:

* Major axis:
* Minor axis:

By this derivation, it is obtained that the standard deviation along the major axis is , indicating that the major axis of the hazard zone dynamically adjusts based on the speed of the equipment. These coefficients are used as initial values in the simulation and are updated based on the simulation results to ensure accuracy. On the other hand, the standard deviation along the minor axis is found to be 3.846, indicating that the minor axis of the hazard zone remains constant regardless of the equipment's speed.

Important notes:

Based on paper (Hazardous Proximity Zone Design for Heavy Construction Excavation Equipment): Although the paper has a very good approach of proposing safety zones, here are some drawbacks:

* Although speed is included as a criterion, there is no way given for dynamically varying the safety zone based on real time data.
* Although the given procedure applies for general case, safety zones are still drawn assuming typical equipment sizes.

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