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Prevention of Falls from Heights in Construction Using an IoT System Based on Fuzzy Markup Language and JFML

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Abstract: The main cause of fatal accidents in the construction sector are falls from height (FFH) and the inappropriate use of a harness is commonly associated with these fatalities. Traditional methods, such as onsite inspections, safety communication, or safety training, are not enough to mitigate accidents caused by FFH associated with a poor management in the use of a harness. Although some technological solutions for the automated monitoring of workers could improve safety conditions, their use is not frequent due to the particularities of construction sites: complexity, dynamic environments, outdoor workplaces, etc. Then, the integration of expert knowledge with technology is a key issue. Fuzzy logic systems (FLS) and Internet of Things (IoT) present many potential benefits, such as real-time decisions being made based on FLS and data from sensors. In the current research, the development and test of an IoT system integrated with the Java Fuzzy Markup Language Library for FLS, to support experts' decision making in FFH, is proposed. The proposal was checked in four construction scenarios based on working conditions with different levels of risk of FFH and obtained promising results.

Keywords: IoT; Fuzzy Markup Language; JFML; fall from height; monitoring; safety; construction

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1. Introduction

Construction workers are traditionally exposed to hazardous activities at construction sites. Evidence of that concern is found in the high accident rates in many countries, as far afield as the United States of America (USA) [1], Norway [2], Spain [3], China [4], and Australia [5]. Special characteristics of the sector include its complexity, dynamic environments, and the exposure to meteorological conditions in outdoor workplaces [6,7], which all contribute to these high accident rates. On a daily basis, risks such as falls from heights (FFH) [8], electrical risks [9], overexertion [10], or being struck by objects [11] are common for construction workers, although the leading cause of fatalities is FFH [12]. As a critical source of fatal accidents, several preventive measures have been developed to reduce occupational FFH, such as guardrails, safety nets, personal protection equipment (PPE) [13], safety training of workers [14], and prevention through design (PtD) [15], in order to reduce risky tasks. Unfortunately, accident trends associated with FFH are not optimistic yet [16].

In spite of all the cited preventive measures, which are important for preventing FFH, in previous research [16] it was found that 89% of those injured were not properly equipped with fall protection devices, such as harnesses and lifelines.

In order to develop adequate safety supervision, automated safety monitoring is considered to be one of the most useful solutions for worker monitoring and safety performance of construction sites [17]. The majority of common safety hazards for construction workers have motivated different monitoring systems based on sensors devices (Table 1).

Table 1. Construction safety hazards and IoT solutions. Adapted from Awolusi et al. [18].

Safety Hazard	Authors	Metric	Sensor
FFH	[19]	Proximity detection	BLE beacon
Slips	[20]	Body orientation, speed and postion	accelerometer
Extreme temperatures	[21]	Corporal temperature	Thermistor
Explosions and fire	[22]	Smoke and fire detection	WIFI
Noise	[23]	Noise level	Smartphone
Strucks	[11]	Distance detection system.	Radio Frequency
Electrocution	[24]	Proximity detection	UWB

Existing technologies provide management opportunities, combining data acquisition processes as techniques to obtain key information from these data.

Nowadays, there is a wide variety of IoT sensor networks to support and improve activities performed by humans. The general structure of wireless sensor networks, several network components, and wireless standards can be found in previous research [25]. In order to summarize existing solutions focused on wireless-based human sensing approaches, previous authors discussed human sensing applications for human activity recognition based on WiFi, Zigbee, BLE, and RFID [26].

Human–computer-interface-based methods are also used in human–computer interface applications. In this sense, the relationship between visual attention and eye-hand coordination [27–29], the effect of different web-based media on human brainwaves [30], and the association between algorithmic problem-solving and executive function [31] have been studied previously.

The great amount of available sensors and the communication between them brings many potential technical solutions to improve safety at the workplace. IoT strategies have been considered as relevant solutions to address the problem. The IoT paradigm describes a system of computing devices that are interrelated and uniquely identified. They are able to communicate data using a network and no human interactions are required [32].

Furthermore, rule-based expert systems based on fuzzy set theory (FLS) [33] have been previously implemented in a wide range of issues. Occupational safety issues based on fuzzy systems were found in previous literature. In this context, some authors proposed a system to evaluate the workers' hazards in the construction environment through a fuzzy-rule-based analysis [34]. A fuzzy system allows one to manage uncertainties associated with occupational risks. Due to the potential benefits of this approach, different proposals for safety assessment in the presence of uncertainty have been developed in other sectors, such as processing industries [35]. Other authors proposed a fuzzy risk assessment method to provide a prevention technique for occupational hazards [36]. Similarly, a method for quantifying occupational safety hazards has been proposed by considering statistical uncertainty inherent in the risk management concept [37].

FLS is appropriate for systems when obtaining a mathematical model and including expert knowledge is very difficult or not possible. Because of this, the IEEE standard for FLS (IEEE Std 1855-2016) was published.

This proposal integrated an IoT infrastructure, automatic data communication from sensors, and JFML for expert decisions. The MQTT protocol is used to communicate information collected from sensors over the IoT architecture. Different types of sensors provide inputs, such as distance, altitude, and wind velocity, from the construction site in real time. The risk of falling from height is represented by a color code, representing the output from the risk assessment: green (low), yellow (medium), orange (high), and red (very high). Additionally, the use of the JFML library integrated with IoT was proposed.

Our paper is structured as follows: Section 2 described the relevant literature regarding FFH, IoT infrastructure, and a brief description of the JFML library. In Section 3, we describe the design and proposal of an infrastructure for FFH risk detection. Section 4 discusses the proposed system with some examples of working situations associated with risks of FFH. In Section 5, conclusions are highlighted.

2. Background

In the current section, an introduction to FFH in the construction sector is presented. Secondly, overviews of the concepts associated with the IoT paradigm are discussed. Lastly, the JFML and its connection with IoT are described.

2.1. FFH Management on Construction Site

Management of a workers' personal fall arrest system (PFAS) is not easy because not all PFAS are compulsory at every location on a construction site. In general, the use of PFAS is regulated by national safety rules, more specifically by safety plans for each construction project. According to the tasks and the risk level of the workplace zone, a PFAS could be compulsory but may not be. For instance, it is not mandatory to connect the harness to the lifeline while workers are working at ground level without risk of falling, but it should be connected to the lifeline once the worker comes into a risky zone, such as a scaffold, a roof, or similar. Sometimes fall arrest systems are not available in dangerous zones; however, a common circumstance is that harnesses can be available at the workplace but they are not properly used [8]. Workers' use or non-use of PFAS is not a random action, because the decision is influenced by different variables [38]. Some authors found that gender, contract forms, and safety training all affected the appropriate use of PPE by construction workers [39]. Similarly, it was found that the influence of organizational factors was important, such as the availability of PPE training on the use of PPE devices, or safety policies regarding PPE, as well as other individual variables, such as knowledge of PPE and personal perception towards the use of PPE [40]. In addition, safety management practices, such as safety supervision, were considered a crucial factor that might influence the use or non-use of PPE [38]. In the particular case of falls, the idea of a fall detection system is not exclusive to workers. A robust fall detection system can contribute in time to addressing a fall in the case of an elderly adult falling at home as well as a worker at work. In any case, IoT solutions to monitoring falls can be classified according to the type of technology used (Table 2).

Table 2. Available technologies for fall detection. Adapted from Singh et al. [41].

Technology	Authors	Proposal	Signal
Wearable sensor	[19]	Monitoring use of Harness by workers	RSSI
Convolutional Neuronal Network	[42]	Detect safety harness wearing	Image
Smartphone sensor	[43]	An algorithm to detect falls based on the Euler angle and acceleration	Acceleration
RGB/IP Image Sensor	[44]	Analyzing human shape deformation during a video sequence	Image

Table 2. *Cont.*

Technology	Authors	Proposal	Signal
Depth Image	[45]	Visualization of human joint analysis for falls detection	Image
Near Field Imaging sensor	[46]	The positioning accuracy is measured using raw observations	RFID
Radar sensor	[47]	Doppler radar-based fall detection system	Eco
Ultrasonic	[48]	Automated system for monitoring human activity using array of heterogeneous ultrasonic sensors	Ultrasounds
Hybrid	[49]	Fusing camera and accelerometer data	Images and aceleration

Each existing system presents advantages, disadvantages, and limitations. For instance, the detection of workers with harnesses based on a convolutional neural network [42] implies a complex installation of the the system, and its use is limited to a reduced number of tasks at height. Similar systems based on image processing [44,45] are limited by the installation of the cameras and configuration of the system in a specific area. These limitations reduce their applicability in dynamic environments, such as in construction sites. Other proposals based on acoustic signals can be very useful at low noise environments [50], but their robustness can be seriously reduced in a noisy environment, such as construction projects. Similarly, the accuracy and robustness of fall detection systems based on Eco [47] and ultrasound systems [48] can be reduced by the presence of unexpected obstacles, and materials obstructing the signal. In addition, the cost of communication infrastructure in a temporary workplace can be particularly high. In contrast, other sensor technologies, such as BLE [51] and RFID [52] are more suitable for applications in construction. The main advantages of these technologies are their easy configuration, good maintainability, accuracy, and stability, and their low power usage [53]. Furthermore, they present high possibilities for integration with other devices [51,54]. In a recent proposal [19], BLE beacons were used to monitor the proper use of PFAS by construction workers; however, some limitations of the system were detected, such as a lack of real time feedback [51]. A description of the previously developed proposal is included in the following sections.

2.2. Internet of Things

The IoT concept can be explained as a system of interrelated computing devices that have the ability to transmit data through a network without requiring human actions [26]. The IoT systems are made up by sensors and actuators to share information, perform tasks together, and to coordinate decisions. Frequently, in an IoT system, three layers are included:

1. *Perception Layer*: Integrates physical devices, such as sensors and actuators. They measure and obtain data and process the information associated with the state of cited devices. In addition, this layer transmits the information of the devices to the upper layers.
2. *Network Layer*: Current layer receives the data from the perception layer and transmits them to the physical devices and applications.
3. *Application Layer*: The information provided by the network layer is received by the application layer, and uses this information in the services and applications developed to work with such data.

The protocol used between the three layers was the Message Queue Telemetry Transport (MQTT) [55]. The MQTT protocol creates connections based on TCP/IP, and they remain open to be reused. Cited protocol is based on a publisher/subscriber architecture.

2.3. IEEE Std 1855-2016 and JFML

The IEEE Std 1855-2016 [56] presents the Fuzzy Markup Language (FML) based on the syntax of the well-defined XML meta-language to represent FLS in a human-readable and hardware-independent way [57]. FML includes an extensible schema that defines the basic components of different types of FLS—including Mamdani, Tsukamoto, and Takagi–Sugeno–Kang (TSK) [58]; also including the most recent AnYa [59].

An FLS described in FML can be divided into the following main five components: fuzzy knowledge base; fuzzy rule base; inference engine; fuzzification subsystem; defuzzification subsystem. Moreover, all components are described by an hierarchy of sub-components in order to fully specify an FLS. All such components are grouped into XML tags with an IP address of devices that compute them, thus enabling networked interoperability among sensors and devices.

JFML library is an open source Java library that allows the design of FLS based on the IEEE Std 1855-2016 [60]. The use of a cited library allows for the implementation of all FLS types enclosed in the standard.

3. IoT-JFML to FFH Proposal

The aim of the proposed system is to prevent FFH suffered by construction workers. The system considers data obtained by different sensors distributed in construction place areas. Data collected by the sensors were associated with significant variables in FFH accidents. Communication between sensors and the rest of the system is based on wireless capabilities. The most relevant factors in FFH were identified and monitored in the present proposal.

- Use of the harnesses. The appropriate use of PFAS is a key factor in FFH that is widely identified in the literature [8,38].
- Altitude. Workplace height is an important variable in FFH. The consequences of FFH accidents are influenced by the altitude of the fall [61].
- Distance to the edge of the fall. A worker placed near to an edge at height is more likely to fall than another located far from the edge in the same workplace. In addition, when workers are placed on elevated surfaces heights, the related changes in their visual field, affect their body balance. There exists a direct relationship between fear of FFH and the actions performed for human postural control [62].
- Wind. Weather conditions are not possible to change in construction sites due to the majority of them being outdoor projects [63]. High wind velocity could impact negatively on construction sites [7].

In order to manage the previously detailed variables, the following sensors and devices were included in the monitoring system.

- BLE receiver (R);
- Harness (H) with BLE integrated for attachment detection (B_0);
- Virtual barrier (VB) of n BLE beacons (B_1, B_2, ..., B_n);
- Altimeter (Alt);
- Anemometer (Anm).

The BLE receiver was designed for IoT systems (R). It provided RSSI values of power for the beacon messages received during the scan phase. According to the RSSI values, the system can calculate the distance between the receivers and beacons [19]. Similarly, a virtual barrier VB with a set of BLE beacons (B_1, B_2, ..., B_n) is used in the proposal [64]. Additionally, the altitude of the workplace was detected by an altitude sensor (Alt) attached to the worker. Moreover, the wind velocity at the workplace is collected by an anemometer (Anm). In Table 3, the information and the working range of the sensors are summarized [65].

Table 3. Sensors description [65].

Sensor	Information	Range
BLE beacon (B_i)	RSSI	0 to −94 dB
BLE Receiver (R)	Distances	0 to 6 m
Altimeter (Alt)	Altitude	0 to 200 m
Anemometer (Anm)	Wind velocity	0 to 150 km/h

According to the sensors and collected information, many working conditions can be evaluated and the risk levels of the tasks performed can be valuated. For instance, the BLE beacon (B_0) joined to the lifeline, combined with a receiver BLE (R), can monitor the connection of the worker connected to the lifeline. Receiver (R) estimates the distance of the worker to the harness anchorage, based on an RSSI signal [19]. When the estimated gap between the worker (R) and the lifeline (B_0) is smaller than a given distance, the harness can be considered connected to the worker.

Considering habitual scenarios, sensors are placed on different working places according to the recommendations of the construction safety experts. Then, the real time information about the worker and their safety conditions are collected and used as input data in the system IOT-JFML. Figure 1 depicts construction workplace with distributed sensors.

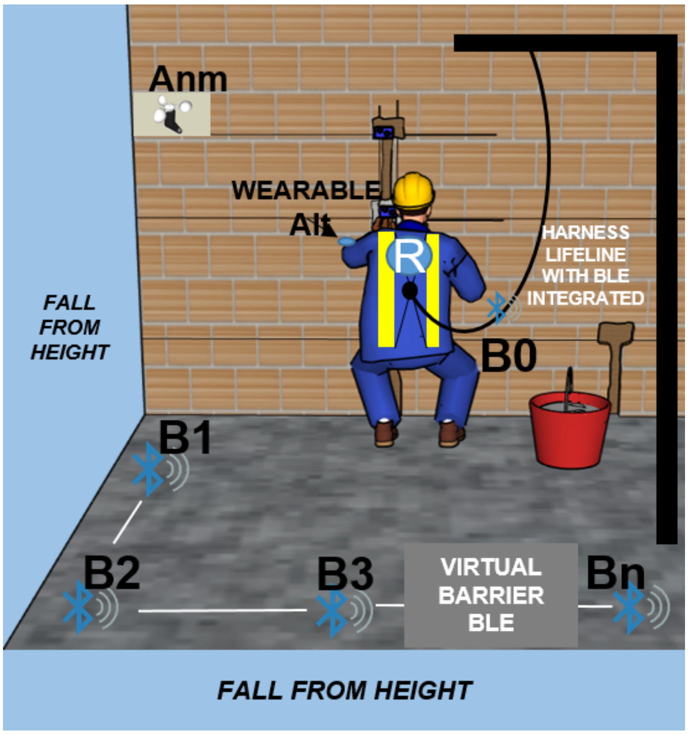

Figure 1. Distribution of the sensors in the construction site.

IOT-JFML Architecture to FFH

The IoT module combined with JFML library provides an IoT infrastructure to generate intelligent IoT solutions under the IEEE std 1855-2016. These advantages were applied in the previous FFH proposal. Figure 2 illustrates a description of the proposed system.

The architecture includes JFML instance, FML file, sensors, actuators, and the broker to act as a conductor between all the elements of the system. The expert knowledge according to the IEEE std 1855-2016 for FFH is represented by the FML file. The sensors and actuators supply information that pass through the MQTT broker which are used for the JFML to make the inference based on the expert knowledge represented in the FML file.

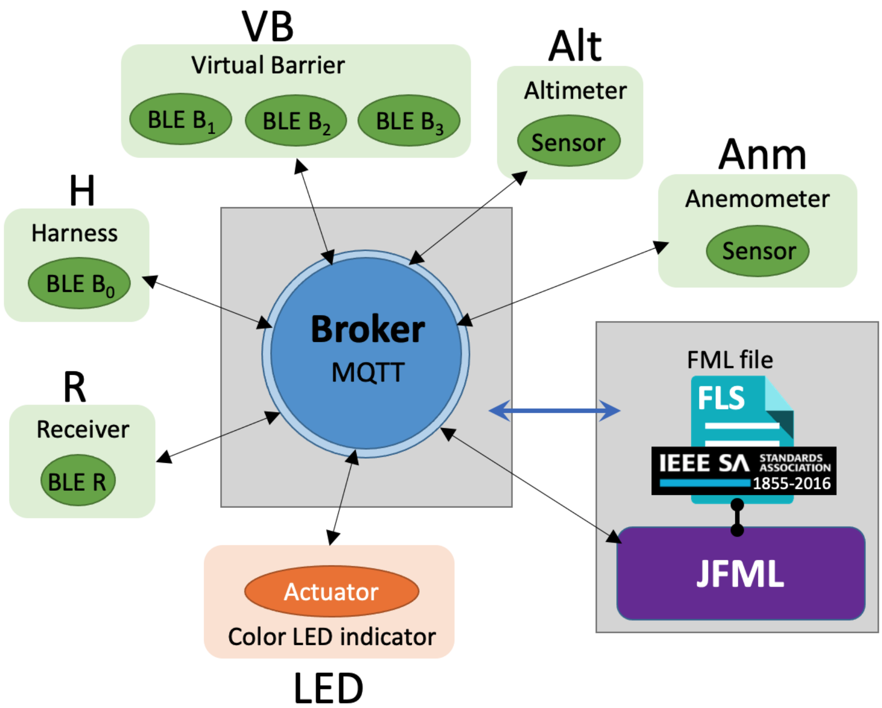

Figure 2. IOT-JFML architecture to FFH.

The MQTT broker is a Mosquitto instance [55] due to it versatility and easy integration with the elements; the JFML library runs on an external computer or in the cloud. The broker and wireless capabilities allow communication between the elements. A common procedure of the communication process is described as follows:

1. Sensors provide data, which publish them into "input" topics. Then, the sensors should be related with their input variables. For instance, the sensor *Anm* publishes data into the topic "*input/Anm*". Similarly, the sensor *Alt* publishes data into the topic "*input/Alt*", etc.
2. JFML is subscribed to all input topics to receive input data from the sensors and to assign them to the input variables. These input variables are defined in the FLS (represented in the FML file according to the IEEE std 1855-2016). For example, JFML is subscribed to the topics "*input/Alt*", "*input/Anm*", etc., to receive data from the sensors *Alt* and *Anm*, respectively. These sensors are associated with the input variables *Altitude* and *Wind velocity*, respectively.
3. The inference is carried out once all of the sensors have published their information and JFML has assigned these values to the input variables. Rules are activated according to the input values and the rule base defined in the FML file.
4. Once the inference process is finished, the output variables obtain values from the corresponding defuzzification method. Then, JFML publishes these values to "output" topics.
5. Actuators receive data, so they are subscribed to "output" topics. As a result, they must be associated with output variables.

4. Case Study

With the aim to test the proposed system, a case study focused on habitual circumstances and tasks performed by construction workers was carried out. The expert knowledge and sensors/actuators were integrated in the proposal. In Section 4.1, the definition of expert knowledge is described; in Section 4.4, some results are presented.

4.1. Characterization of the Fuzzy Logic System

Many construction site scenarios and their level of occupational risks can be evaluated by employing the designed IOT-JFML system. To do that, first, the FLS must be defined where expert knowledge on FFH is considered in order to select variables to support the problem at hand.

Then, with the aim to clarify the definition of an FLS for FFH, where the OHS legislation, expert knowledge on FFH, input variables, their association to gradual concepts by means of fuzzy logic, etc., a methodology was defined. Based on the information gathered, tentative rules are proposed and reviewed by a panel of experts in this field of knowledge (eight persons with expert knowledge on FFH). If the experts do not validate the rules, the process is initiated in order to propose new variables and rules; however, if the proposal is validated, a fuzzy logic system is defined. Figure 3 illustrates the procedure to define the FLS and to model it according to the IEEE std 1855-2016.

Notice that the aim of the IEEE std 1855-2016 for Fuzzy Markup Language is to provide the research community a human-readable and hardware independent way to represent an FLS. This standard includes several fuzzification methods and inference systems. In this paper, since the objective is to propose a distributed approach that collects sensor data and automatically and intelligently acts by considering expert knowledge in FFH, we use Mamdani as an inference method and COA as a defuzzification method since they are the most widely used in this type of problem [58,66]. In the same way, we use trapezoid membership functions to model fuzzy terms due to they model fuzzy terms adequately in a gradual domain.

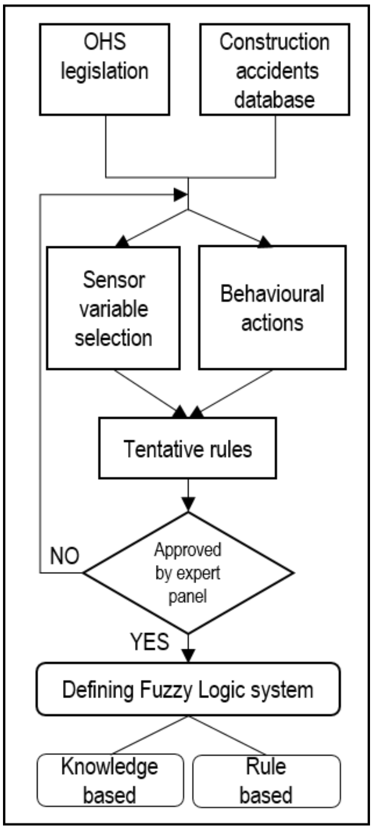

Figure 3. Definition of the FLS.

The knowledge base with different fuzzy variables and their fuzzy terms are stated first (Section 4.1.1). Then, considering the expert knowledge and the relations between the fuzzy variables, the rule base is also defined (Section 4.2). Last, according to the IEEE std 1855-2016 for Fuzzy Markup Language, an FLS representation is described (Section 4.3).

4.1.1. Determining the Knowledge Base

To determine the knowledge base, expert knowledge on FFH is considered in order to select variables to support the problem at hand. For example, a worker closer than 75 cm to his/her lifeline is defined as attached. Similarly, if a construction worker is closer than 50 cm to an edge defined by a virtual barrier of beacons, the risk of FFH is accepted as high. If the worker is farther, the risk value will be medium or low. Then, to manage this gradual concept on the distance, domain fuzzy variables associated with sensors and actuators are characterized (four input and one output):

- *Harness detection* is associated with appropriate use of the hardness by the construction worker. The values of the input variable are: *"Attached"*, *"Unattached"*.
- *Virtual fence distance* depicts the average distance of the construction worker to the virtual barrier. Then, the input variable is composed of the fuzzy terms *"Near"*, *"Medium"*, and *"Far"* in the domain $[0, 200]$ and expressed in centimeters.
- *Altitude* is defined as the related distance between the ground level and the worker. It is an input variable defined by the fuzzy terms *"Little"*, *"Medium"*, or *"Tall"* in the domain $[0, 15]$ represented in meters.
- *Wind velocity* is the speed of the wind in the construction place. An input variable defined by the fuzzy terms *"Low"*, *"Medium"*, or *"High"* in the domain $[0, 120]$ and represented in km/h.
- *Risk* represents the level of FFH risk. It is an output variable defined by the fuzzy terms *"Low Risk"*, *"Medium Risk"*, *"High Risk"*, and *"Very High Risk"* in the domain $[0, 10]$.

Table 4 shows the different variables described and their relation with respect to the level of FFH risk.

Table 4. Variables and level of FFH risk.

Variable	Low Risk	Medium Risk	High Risk
Detection of the Harness	attached	-	unattached
Distance to the Virtual fence	≥150 cm	150–50 cm	≤50 cm
Altitude	0–1 m	1–2 m	≤2 m
Wind velocity	≥0–15 km/h	16–30 km/h	≤30 km/h

4.2. Determining the Rule Base

To determine the level of risk, the expert knowledge of the FFH in a construction scenario in the form of rules is considered. A group of safety managers stated many levels of risk based on their experience. They stated five levels of risk (very low, low, medium, high, and very high risk). According to this levels defined by the experts, five fuzzy sets in the domain [0, 10] are stated and illustrated in Figure 4.

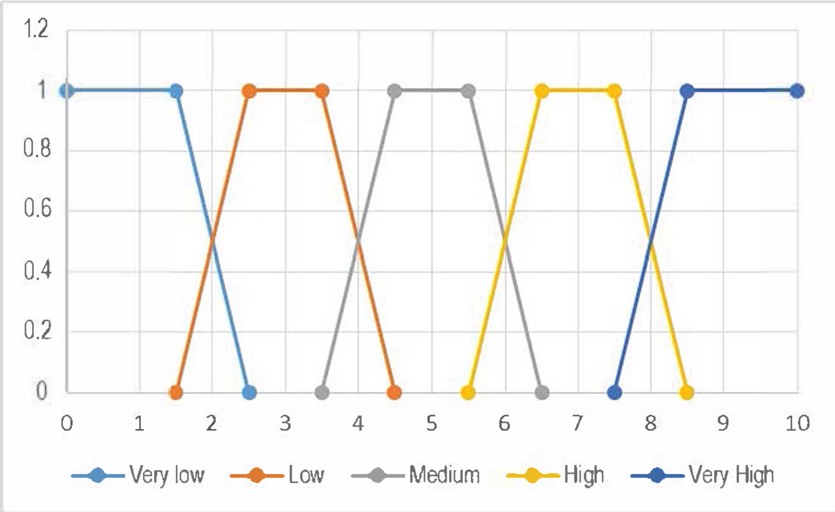

Figure 4. Definition of fuzzy risk levels.

Moreover, the panel of experts suggested different rules to pattern these risk situations. Specifically, after the methodology, to define the FLS mentioned before, and illustrated in Figure 3, they proposed 11 rules. For a better understanding, some of the cited rules are enumerated below.

1. *IF Virtual fence distance IS Far THEN Risk IS Low*
2. *IF Virtual fence distance IS Medium AND Harness detection IS attached THEN Risk IS Low*
   ...
4. *IF Virtual fence distance IS Medium AND Harness detection IS unattached AND Altitude IS Little THEN Risk IS Low*
   ...
7. *IF Virtual fence distance IS Near AND Wind velocity IS High THEN Risk IS Medium*
   ...
11. *IF Wind velocity IS very High AND Altitude IS High THEN Risk IS Very High*

4.3. Fuzzy Logic System According to the IEEE 1855-2016

The described fuzzy variables and rules were represented in a FML file according to the IEEE std 1855-2016 specifications. As an illustrative example, some parts of the file are shown in the Code 1.

```xml
<?xml version="1.0" encoding="UTF-8"?>
<fuzzySystem xmlns="http://www.ieee1855.org" name=
    "FFH risk - Example">
    <knowledgeBase>
        <fuzzyVariable name="Harness detection"
    domainleft="0.0" domainright="1.0" type="input
    ">
            <fuzzyTerm name="attached">
                <singletonShape param1="1.0"/>
            </fuzzyTerm>
            <fuzzyTerm name="unattached">
                <singletonShape param1="0.0"/>
            </fuzzyTerm>
        </fuzzyVariable>
                ...
    </knowledgeBase>
    <mamdaniRuleBase name="rulebase1"
    activationMethod="MIN" andMethod="MIN"
    orMethod="MAX">
        <rule name="rule1" andMethod="MIN"
    connector="and" weight="1.0">
            <antecedent>
                <clause>
                    <variable>Virtual fence
    distance</variable>
                    <term>High</term>
                </clause>
            </antecedent>
            <consequent>
                <then>
                    <clause>
                        <variable>Risk</variable>
                        <term>Low</term>
                    </clause>
                </then>
            </consequent>
        </rule>
                ...
    </mamdaniRuleBase>
</fuzzySystem>
```

Code 1. Extract of FML file according to the IEEE std 1855-2016 designed for the fall from height.

4.4. Results from Different Construction Scenarios

In current subsection, the IOT-JFML system was tested in four different simulated scenarios at construction sites. In the analyzed scenarios, sensors provided data, JFML received them and the actuators acted based on the output values generated by both the JFML and the FLS for FFH. Additionally, a group of OHS experts evaluated the results provided by the system.

Due to ethical and safety reasons, experiments in real construction sites were not possible. It is illogical and irresponsible to generate occupational risks in order to test preventive measures. In consequence, the system were only tested using virtual scenarios.

4.4.1. Case 1: Working at Ground Level

Several construction activities performed at ground level are influenced by the risk of FFH. For instance, when there are excavation works, or when the basement is built. The current case described a task situation with a worker placed far away from the virtual barrier of beacons. Beacons were placed near to the edge of the fall, to delimit the safety area. Figure 5 describes a graphical view of this scenario.

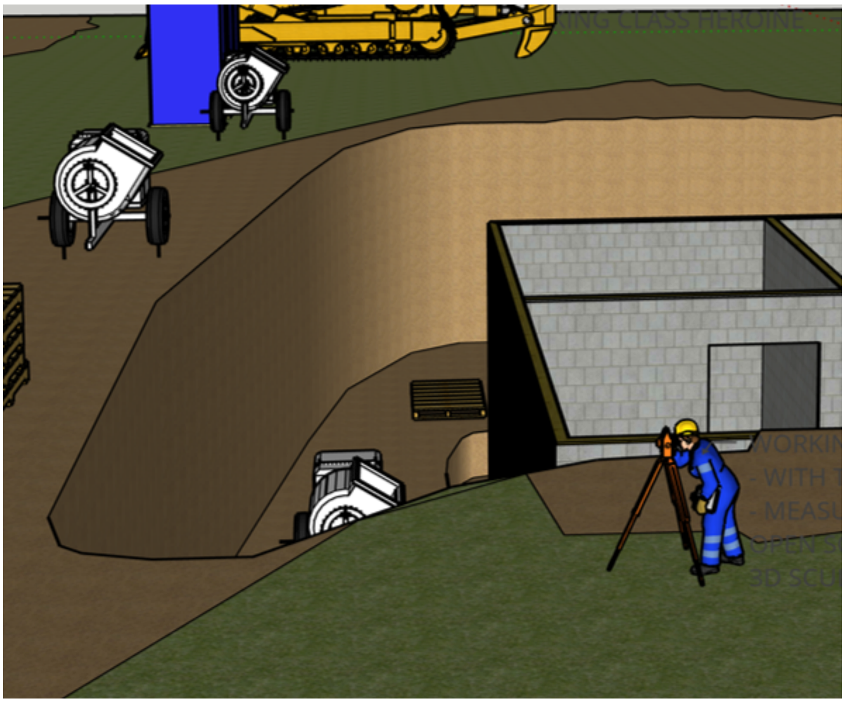

Figure 5. Visual example of fall from ground level to lower level.

The altitude from the level of the worker to the next lower level was approximately 1 m and the wind factor was considered medium (10 km/h). The harness was attached and the distance to the virtual fence was 150 cm. In the described situation, and using the described values as input data, the risk value estimated was 2.9999 (Figure 6). This scenario fired Rule 1 with a weight of 75% corresponding to a far distance with the virtual fence and Rule 2 (25% weight) corresponding to the harness connected; as a result, the risk was low. These estimated values are aligned with the expert panel values for this scenario.

```
RESULTS
(INPUT): Harness_detection=1.0,
   Virtual_fence_distance=150.0, Altitude=1.0,
   Wind_velocity=10.0
(OUTPUT): Risk=2.9999995
(ACTIVATED RULES):
  RULE 1: rule1 - (0.75) IF
   Virtual_fence_distance IS Far THEN Risk IS Low
    [weight=1.0]
  RULE 2: rule2 - (0.25) IF
   Virtual_fence_distance IS Medium AND
   Harness_detection IS Attached THEN Risk IS Low
    [weight=1.0]
```

Figure 6. Risk levels estimated by the system for the scenario 1 (ground level to lower level).

Previous authors pointed the influence in the risk levels of dangerous activities, such as assembly and disassembly of temporary structures [67,68]. In the scenario analyzed, the absence of cited dangerous activities and the low altitude of the tasks performed, motivated low risk values. Then, risk values obtained by the system are aligned with previous results and safety experts' opinion.

In this scenario, other technological solutions are possible. For instance, location of the worker using a GPS device could be applied in order to alert a dangerous situation of the worker near to the falling zone [69]; however, the configuration of the system will be complex, and the accuracy of the GPS signal could not be enough for an adequate management of the FFH risk [51].

4.4.2. Case 2: Formwork Activities

In the next scenario, a common building situation was described: workers assembling manual formwork structures and placing the slab formwork. Formwork tasks have been highlighted as a source of occupational risks in construction projects, by different authors [70]. FFH was pointed to as the most dangerous risk [68]. Figure 7 illustrates a visual example of this scenario.

In this example, the worker is manually assembling the formwork structure. They are situated attached to the lifeline and close to the harness and BLE barrier. In the described scenario, the risk value provided by the group of OHS experts is medium. The wind velocity was scored as 30 km/h, the harness was attached and the virtual fence distance was 20 cm. The IoT-JFML system risk score was 5.000014 (Figure 8). This scenario fires Rule 7 with a weight of 100% corresponding to a close BLE barrier being near and the harness detection being connected, so the risk value estimated is medium. Again, this result matched with the results provided by the expert panel.

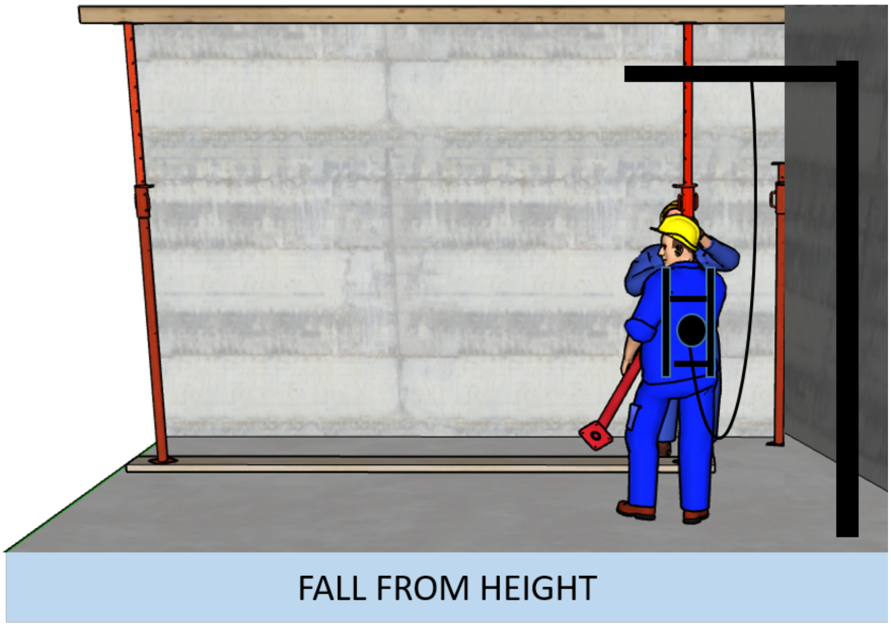

Figure 7. Visual example of fall from a building floor.

```
RESULTS
(INPUT): Harness_detection=1.0,
   Virtual_fence_distance=20.0, Altitude=1.0,
   Wind_velocity=30.0
(OUTPUT): Risk=5.000014
(ACTIVATED RULES):
  RULE 7: rule7 - (1.0) IF Virtual_fence_distance
    IS Near AND Harness_detection IS Attached
    THEN Risk IS Medium [weight=1.0]
```

Figure 8. Results provided by the IOT-JFML system for Scenario 1 (ground level to lower level).

Existing technologies could provide alternative solutions to mitigate FFH risk in tasks related to formworks. Some authors propose the combination of BIM and IoT systems [71]; however, continuous monitoring of the worker using visual monitoring system is more expensive that our proposal. In addition the integration of IoT with BIM is complex to install and to configure.

4.4.3. Case 3: Scaffolding Tasks

A construction site with the presence of the worker on a scaffold was studied. The presence of scaffolds is very common in construction tasks (facades, upper levels, and roofing). Scaffolds are one of the major sources of fatal falls in construction [72]. The majority of accidents related with scaffolding are probably very serious or fatal due to the hazardous working conditions [73]. Then, other authors assessed the safety-risk-related scaffolding tasks, based on the accidents research, the identification habitual scaffolding accidents situations, and the evaluation of the probability of accidents [68,74]. Based on that, a scenario related with scaffolding was modeled and tested (Figure 9).

Figure 9. Visual example of fall from scaffolding activities.

In this scenario, a worker was working on the scaffold. He had harness unattached and he was close to the BLE fence. The altitude value was 12 m, while the wind value was 25 km/h. Although there is a safety rail guard on the scaffold, there are some areas in this scenario without collective protection. The risk score of the proposal was 7.424078 and Rule 10 and Rule 11 were fired with weight 75% and 25%, respectively (Figure 10). In this scenario, the risk score obtained is high due to high altitude and wind velocity. Similarly, the values estimated by OHS experts in these circumstances where aligned with scores from the IoT-JFML system. Expert values are based on the lack or the misuse of the harness at construction sites. Previous authors found that a high percentage of fall accident victims did not use fall protection [75]. In the same study, it was concluded that fall protection use and injury class were associated with statistical significance. These results are aligned with similar studies [8].

In regard to scaffolding tasks, some authors proposed the prevention of FFH using computer vision and IoT-based monitoring [76]. Their experimental results showed high accuracy in the tested scenarios. The main disadvantage of the cited solution is that the necessary infrastructure for computer vision devices is complex and their configuration is expensive. Moreover, scenarios with confusing images as a consequence of insufficient light or more workers in the same picture cannot be suitable for this technology.

```
RESULTS
(INPUT): Harness_detection=0.0,
   Virtual_fence_distance=4.0, Altitude=12.0,
   Wind_velocity=25.0
(OUTPUT): Risk=7.424078
(ACTIVATED RULES):
  RULE 10: rule10 - (0.75) IF
   Virtual_fence_distance IS Near AND
   Harness_detection IS Unattached AND Altitude IS
   Tall AND Wind_velocity IS Medium THEN Risk IS
   High [weight=1.0]
  RULE 11: rule11 - (0.25) IF
   Virtual_fence_distance IS Near AND
   Harness_detection IS Unattached AND Altitude IS
   Tall AND Wind_velocity IS High THEN Risk IS
   Very High [weight=1.0]
```

Figure 10. Risk levels estimated by the system for Scenario 3 (scaffolding tasks).

4.4.4. Case 4: Roofing Tasks

The forth scenario was associated with roofing activities. Different authors associated roofing tasks with FFH [8,12,77]. Falls from a roof are linked to fatal consequences [78], but their workers do not often use PFA systems. The employment of fall protection systems between workers has been demonstrated as a negative impact on the productivity of the workers [79]. In order to address the problem, technological solutions could be used [80]. Safety training in the use of PPE might be an effective strategy too, since the residential roofers experienced worse fatality rates than commercial roofers [81].

Figure 11 illustrates a roofing scenario with a construction worker on it.

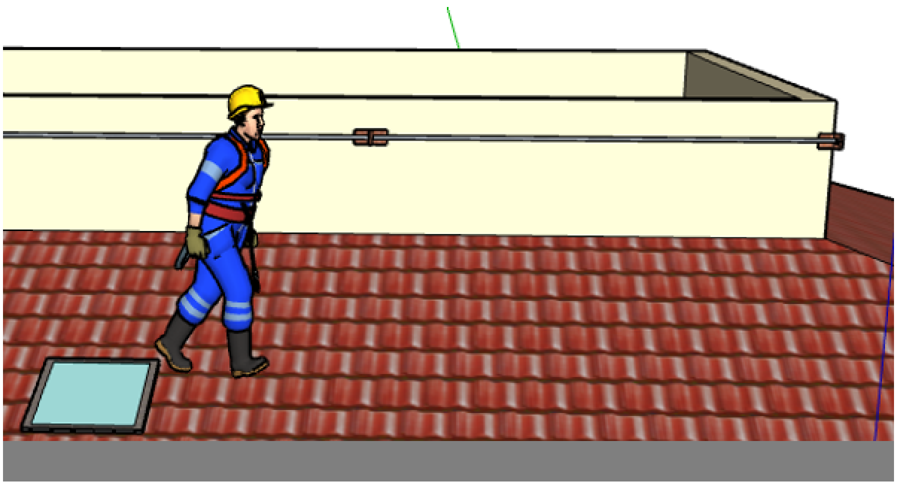

Figure 11. Visual example of fall from roof.

In current example, the worker has no harness attached. They were placed close to the BLE fence. Their altitude was 15 m and the wind velocity was about 50 km/h. The risk calculated by the proposal was 8.979336 and Rule 11 was fired with a weight of 100% (Figure 12). In this case, the risk was very high and the system gave a result similar to the group of experts, who considered this working situation as very high risk.

Results are aligned with previous studies that pointed to roofing as one of the most important activities that lead to FFH on construction sites [12,77].

```
RESULTS
 (INPUT): Harness_detection=0.0,
    Virtual_fence_distance=4.0, Altitude=15.0,
    Wind_velocity=50.0
 (OUTPUT): Risk=8.979336
 (ACTIVATED RULES):
   RULE 11: rule11 - (1.0) IF
    Virtual_fence_distance IS Near AND Harness_detection IS
    Unattached AND Altitude IS Tall AND Wind_velocity IS High
    THEN Risk IS Very_High [weight=1.0]
```

Figure 12. Risk levels estimated by the system for Scenario 4 (roofing tasks).

5. Conclusions

In this paper, the combination of Fuzzy Markup Language on JFML and IoT infrastructure has been integrated in a proposed system and tested to prevent FFH at construction sites.

Firstly, the most relevant factors for FFH in a construction environment were identified. Specifically, the correct use of a harness, the altitude, the distance to the edge of the fall, and the wind velocity have all been considered. Secondly, several sensors have been employed to collect information about these factors (anemometer, beacons, altimeter, etc.). In addition, an architecture based on the IoT paradigm has been considered and detailed. A panel of experts were consulted to evaluate the risk situations and to check the proposed system. On the basis of their knowledge, a fuzzy logic system (FLS), where some fuzzy rules based on fuzzy variables have been designed and implemented according to the IEEE std 1855-2016, was to be run with JFML. Four input variables and one output fuzzy variable were described and defined. A total of 11 fuzzy rules were defined.

In addition, in order to determine the advantages of the proposed system, four different scenarios based on habitual working situations with a risk of FFH were tested and evaluated by a panel of experts. In the first scenario proposed, the worker could fall to an underground level. In the second scenario, the worker was assembling formworks in a building structure. In the third scenario, the worker was developing tasks on a temporary scaffold. In the last one, the case of a worker on a roof was considered.

It is remarkable that at least one rule defined in the FLS and related to the harness detection was fired in the four scenario simulated. As a consequence, the management of the appropriate use of the harness in dangerous zones is a key aspect to prevent FFH. This conclusion is aligned with previous studies focused on the prevention of FFH in construction sector.

The results obtained are relevant in the field of safety at work and are in accordance with the panel of experts. The proposed system is flexible and scalable. The system could be expanded with the integration of new specific sensors in order to obtain information on other occupational risks in construction projects. For example, ultra-wideband sensors could provide the distance between the worker and heavy equipment. The extension of the system would not be complex. New sensors can be connected to the broker. Tentative new rules would be defined, and after approval by the expert panel, they can be integrated into the FLS.

It should be noted that the IOT-JFML system was performed for only one construction worker, although its applicability can be extended to a greater number of construction workers. As a consequence in future research, it could applied to a group of workers in different workplace scenarios. The information provided can help to coordinate construction safety practices.

The key advantage of the proposal is its real-time capacity to evaluate the levels of risk to the construction workers, according to the values obtained by the sensors. It is an important advance when compared with traditional risk assessment, where the majority of risk is evaluated before the beginning of the construction project; however, the FFH risk level can change in dynamic environments such as a construction site. Then, the continuous monitoring of the workers in a wireless way, considering the main variables of FFH, provides the option to update construction risk levels in real time.

The proposed system could improve the risk perception by workers and managers because risk levels are based on real data, in contrast to traditional methods, which are based on estimated data obtained from formal construction projects and not from real construction sites. Work instructions from safety coordinators based on real time data supplied by the IOT-JFML proposal will improve construction site safety levels. In this sense, future safety training programs could be adapted to the risk exposure suffered by the different workers profiles, according to the risk levels monitored by the IOT-JFML system.

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