

Research Article

Forest Fire Prevention, Detection, and Fighting Based on Fuzzy Logic and Wireless Sensor Networks

Josué Toledo-Castro ¹, **Pino Caballero-Gil** ¹,
Nayra Rodríguez-Pérez ¹, **Iván Santos-González** ¹,
Candelaria Hernández-Goya ¹ and **Ricardo Aguasca-Colomo** ²

¹Department of Computer Engineering and Systems, University of La Laguna, 38206 Tenerife, Spain

²Instituto Universitario de Sistemas Inteligentes y Aplicaciones Numéricas en Ingeniería, University of Las Palmas de Gran Canaria, 35017 Gran Canaria, Spain

Correspondence should be addressed to Josué Toledo-Castro; jtoledoc@ull.edu.es

Received 6 August 2018; Accepted 11 November 2018; Published 2 December 2018

Guest Editor: Andrew Schumann

Copyright © 2018 Josué Toledo-Castro et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Huge losses and serious threats to ecosystems are common consequences of forest fires. This work describes a forest fire controller based on fuzzy logic and decision-making methods aiming at enhancing forest fire prevention, detection, and fighting systems. In the proposal, the environmental monitoring of several dynamic risk factors is performed with wireless sensor networks and analysed with the proposed fuzzy-based controller. With respect to this, meteorological variables, polluting gases and the oxygen level are measured in real time to estimate the existence of forest fire risks in the short-term and to detect the recent occurrence of fire outbreaks over different forest areas. Besides, the Analytic Hierarchy Process method is used to determine the level of fire spread, and, when necessary, environmental alerts are sent by a Web service and received by a mobile application. For this purpose, integrity, confidentiality, and authenticity of environmental information and alerts are protected with implementations of Lamport's authentication scheme, Diffie-Lamport signature, and AES-CBC block cipher.

1. Introduction

Nowadays, forest fires often cause serious threats to the environment and produce real emergency situations and natural disasters. The response time of emergency corps greatly affects the consequences and losses caused by them, so the enhancement of forest fire prevention and detection systems can be considered a main goal for conserving the environment. With respect to this, the real-time monitoring of certain environmental variables may make the forest fire prevention, detection, and fighting more efficient.

Different types of environmental risk factors can be considered for estimating the existence of forest fire risks over different forest areas. On the one hand, static forest fire risk factors such as vegetation layers, topography, or the frequency of forest fires may be useful to perform a long-term estimation of forest fire risks because vegetation

affected by weather changes over time and several topography parameters (such as the existence of elevated slopes) may have a direct impact on the probability of fire occurrence. On the other hand, unusual changes of dynamic forest fire risks such as meteorological variables, polluting gases, or the oxygen level measured in real time can be analysed aiming at performing a short-term estimation of forest fire risks. Likewise, uncommon decrease of humidity values or oxygen level jointly with increasing temperature values or the concentrations of certain polluting gases, such as carbon dioxide and carbon monoxide, may involve a high probability of outbreaks of recent nearby fires. Therefore, environmental monitoring may make the response time of emergency corps more efficient. Fire spread can be also estimated by analysing the values of meteorological variables, wind direction changes, and the oxygen level over nearby forest areas, because these variables have a direct impact on

relevant fire propagation factors such as dryness of vegetation and organic fuels.

A wireless sensor network (WSN) [1] based on Internet of Things (IoT) devices and sensors can be used to perform a real-time environmental monitoring of the aforementioned forest fire risk factors. Their design and distribution have to be addressed aiming at covering as much forest areas as possible. With respect to this, several challenges must be considered, such as the authentication of sensor nodes [2] and the security of wireless communications among distributed sensor nodes, taking into account possible areas out of network coverage.

Due to the uncertainty in environmental data, understanding environmental changes to estimate the existence of fire risks or to detect the occurrence of a wildfire incident is not a simple process that can be executed with complete accuracy. Fuzzy logic [3] and decision-making methods such as the Analytic Hierarchy Process (AHP) [4] can be used to provide an enhancement in the real-time analysis of environmental data. Forest fire prevention and detection may be more accurate through the interpretation of the forest fire risks involved in every measured environmental variable jointly with unusual environmental changes with respect to the typical values measured by a WSN.

The main goal of the proposal here described is to estimate in short-term the existence of forest fire risks and to detect the recent occurrence of fire outbreaks over different forest areas. For this purpose, a forest fire controller based on fuzzy logic has been implemented aiming at analysing environmental information, such as meteorological variables, polluting gases, and the oxygen level, measured by a distributed WSN. To this end, a particular prototype of IoT device equipped with environmental sensors has been implemented. When a fire outbreak is detected, a decision-making method based on AHP is enabled to determine the neighbouring forest area that is more likely to favour fire spread as a result of its current environmental conditions. Moreover, a Web service and a mobile application have been implemented aiming at activating environmental alerts. Besides, open data sources have been integrated to provide other relevant environmental information such as vegetation layers or historical information of recent fires. Particular attention has been paid to the application of security mechanisms to protect the integrity, confidentiality, and authenticity of measured environmental information and alerts through implementations of Lamport's authentication scheme [5], Diffie-Lamport's signature [6], and AES-CBC block cipher [7].

This work is organized as follows. Section 2 deals with some related works. Section 3 details the proposed forest fire controller based on fuzzy logic. Section 4 outlines the AHP-based detection method of fire spread. Then, the proposed system is explained in Section 5 and the implemented security mechanisms are sketched in Section 6. Section 7 includes a description of several experimental results. Finally, some conclusions and research works in progress are given in Section 8.

2. Related Works

In the last years, different proposals have been put forward to improve forest fire prevention, detection, and extinction

systems. Many of those solutions are based on real-time environmental monitoring and IoT devices. With respect to this, the work [8] includes the implementation of a smart system aiming at measuring carbon dioxide (CO₂) emissions from different sources such as forest fires through using Raspberry Pi. In addition to monitoring polluting gases, other proposals analyse the so-called Fire Weather Index for designing an efficient fire detection system through wireless sensor networks and a simple data aggregation scheme [9].

Nowadays, the combination of fuzzy logic and decision-making methods, such as AHP, produces innovative solutions that may enhance the accuracy in the prevention and detection of wildfire incidents.

The work [10] proposes a fuzzy system based on overlap indices to improve forest fire detection through implementing a wireless sensor network and analysing different variables such as the lightness and the distance to the fire. In that work, a particular generalization of the Mamdani inference system is introduced by using overlap functions and overlap indices. Likewise, the work [11] also proposes the use of WSNs and the incorporation of fuzzy logic in sensor nodes but its aim is to estimate the evidence of fire through analysing the previous temperature and the current temperature. For that purpose, two fuzzy approaches based on temporal characteristics are proposed to optimize the number of rules that have to be checked.

Regarding the use of decision-making algorithms, the work [12] includes a model of the forest fire risk through integrating fuzzy sets with AHP. In particular, it uses a decision-making method including the Geographic Information System and the fuzzy AHP method [13] to estimate the importance related to each considered causative factor in forest fires.

The security and the distribution of the WSN require particular attention [14, 15]. Several security challenges and threats are addressed in [16] with respect to wireless communication. The survey [17] includes recent routing protocols and presents a classification in categories such as data-centric, hierarchical, and location-based. Likewise, the functional design and the implementation of a complete WSN platform are presented in [18] aiming at performing a long-term environmental monitoring. Low cost, minimum number of sensors, fast deployment, and other requirements are also considered in the approach of WSN design in different works.

Differently from the aforementioned works, the system described here proposes the combination of WSN, fuzzy logic, decision-making methods, multihop routing [19], and security mechanisms for performing a secure real-time environmental monitoring of dynamic forest fire risk factors. The main aim is to estimate the existing forest fire risks in different monitored forest areas and to detect the occurrence of fire outbreaks. Moreover, a decision-method based on AHP intended to determine the fire spread through nearby forest areas has been implemented in a system composed by a Web service and a mobile application to manage environmental alerts and provide an enhancement in forest fire prevention, detection, and tracking systems.

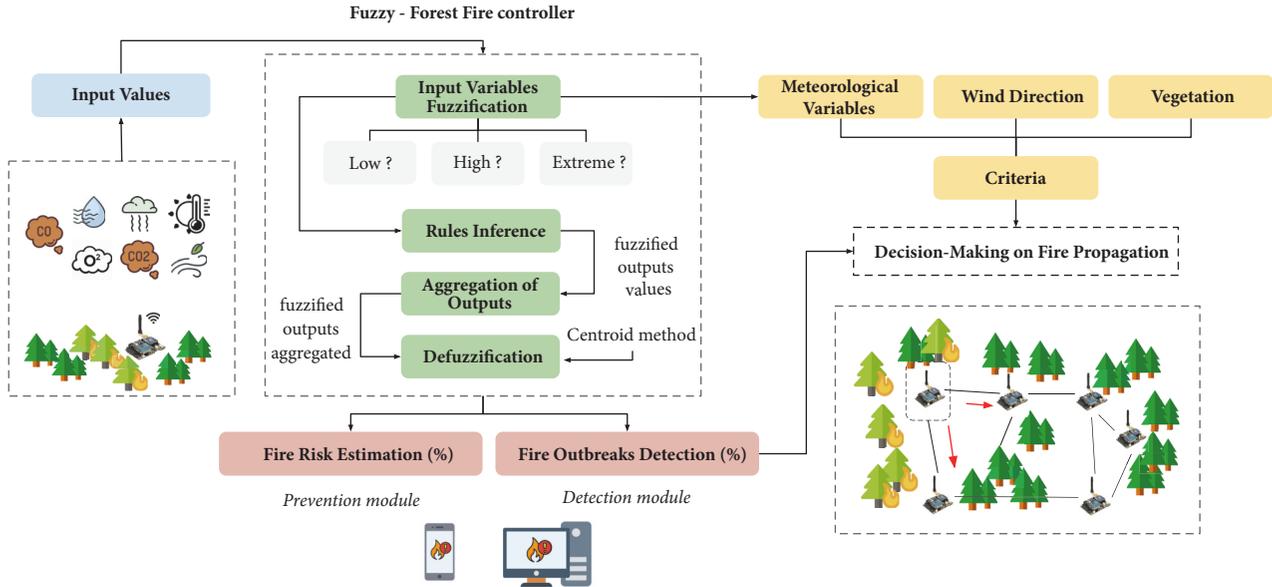


FIGURE 1: Fuzzy-based forest fire controller and AHP-based fire spread estimator.

3. Fuzzy-Based Forest Fire Controller

The proposed method is based on environmental measurements of dynamic forest fire risk factors such as meteorological variables, polluting gases, and oxygen level measured by a distributed WSN in real time. The aim is to provide an enhancement in the short-term estimation of forest fire risks (prevention) and in the detection of the beginning of recent wildfire incidents (detection). With respect to this, a fuzzy-based forest fire controller has been implemented aiming at calculating the probability of existing forest fire risks (prevention module) and the probability that a fire outbreak has recently occurred (detection module) in a particular forest area. On the one hand, the prevention module is intended to analyse measured environmental conditions that may favour the occurrence of a wildfire incident (high temperatures, low relative humidity values, vegetation dryness due to low rainfall, etc.). On the other hand, the detection module is aimed at detecting wildfire incidents that have recently occurred. In addition to meteorological variables, the oxygen level and the concentrations of polluting gases (useful indicators of fire outbreaks occurrence and biomass burning process) measured by the WSN are also analysed. Thus, unusual environmental changes such as temperature increase and decrease in relative humidity and oxygen values jointly with very high concentrations of carbon dioxide and carbon monoxide may involve the recent occurrence of a forest fire.

In order to face the difficulty and imprecision of the analysis of environmental changes related to forest fires, a fuzzy logic Mamdani inference system [20] has been considered aiming at developing a forest fire controller. As Figure 1 shows, environmental values measured by the deployed WSN are initially fuzzified to provide a level of membership with different fuzzy sets proposed for each

TABLE 1: Notation used to describe the fuzzy-based forest fire controller.

Notations	Description
v	Linguistic variable
α_v	Discrete measurement of v
FD_v	Fuzzy Domain of v
FS_{v_i}	i -th Fuzzy Set proposed for v
$\mu_{FS_{v_i}}(\alpha_v)$	Level of membership of α_v with respect to FS_{v_i}

considered linguistic variable. These fuzzy sets are intended to express if a particular measurement may be “normal”, “low”, “high”, or “extreme” depending on the common state of the corresponding analysed environmental variable. Each fuzzified measure is evaluated on the basis of a knowledge base or inference rules to analyse the related forest fire risks and the probability of fire outbreaks occurrence. Finally, the obtained results are aggregated into a same output set and defuzzified into a discrete percentage.

Mamdani’s inference steps are described using the notation in Table 1.

3.1. Input Variables Fuzzification. Dynamic forest fire risk factors are considered as input linguistic variables of the proposed fuzzy-based forest fire controller. With respect to this, the corresponding environmental measurements registered by the distributed WSN for meteorological variables, polluting gases, and the oxygen represent the input values of the proposed fuzzy system.

Measurements of temperature, relative humidity, wind speed, and rainfall are fuzzified into the membership function proposed for each one of these monitored meteorological

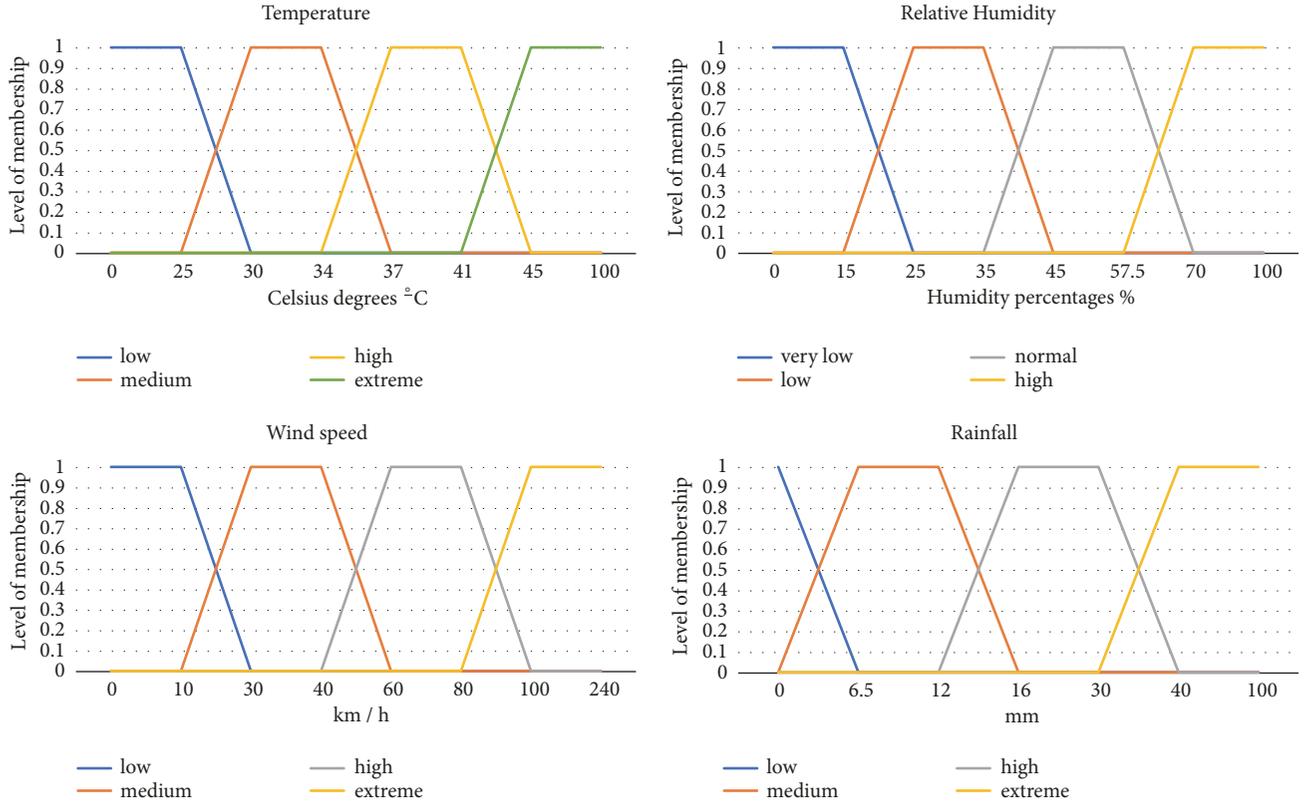


FIGURE 2: Membership functions of meteorological variables.

TABLE 2: Fuzzy sets and fuzzy domains proposed for every linguistic variable.

Variable	Fuzzy Set	Fuzzy Domain
Temperature (T)	$FS_T = \{\text{low, medium, high, extreme}\}$	$[0, 100]$ °C
Humidity (H)	$FS_H = \{\text{very low, low, normal, high}\}$	$[0 - 100]$ %
Wind Speed (W_{speed})	$FS_{W_{speed}} = \{\text{low, medium, high, extreme}\}$	$[0 - 240]$ km/h
Rainfall (R)	$FS_R = \{\text{low, medium, high, extreme}\}$	$[0-100]$ mm
Oxygen (O_2)	$FS_{O_2} = \{\text{very low, low, normal, high}\}$	$[0-30]$ %
Carbon dioxide (CO_2)	$FS_{CO_2} = \{\text{low, normal, high, extreme}\}$	$[0-1000]$ ppm
Carbon monoxide (CO)	$FS_{CO} = \{\text{normal, medium, high, extreme}\}$	$[0-100]$ ppm

variables (see Figure 2). The graphical representation of the membership function of each linguistic variable is performed on an ordinate axis that represents the level of membership of measured input values with the different proposed fuzzy sets. On the other hand, the abscissa axis represents the domain of the linguistic variable regarding its discourse of universe (Celsius degrees, percentages, km/h, etc.). The main aim is to express the fuzzified value attached to every environmental measurement as “very low”, “low”, “normal”, “high”, or “extreme”.

The rule of 30, considered as a relevant preventive model of forest fire risk, has been applied here to design fuzzy sets. This rule considers measurements of temperature and wind speed above 30°C and 30 km/h, respectively, jointly with humidity values below 30 % as risk environmental conditions that may favour the occurrence of forest fires.

Regarding fire outbreak detection provided by the proposed fuzzy-based forest fire controller, measurements of oxygen level, and polluting gases (carbon dioxide and carbon monoxide) are also fuzzified into their corresponding membership functions. In the case of polluting gases, particles per million (ppm) are used as their discourse of universe. Their fuzzy sets have been proposed on the basis of unusual increases above their typical environmental concentrations at outdoor forest areas (see Figure 3). In contrast, unexpected decreases of the oxygen level below 21 % levels (considered as the current measured oxygen level at the atmosphere) have been considered for their design. These uncommon environmental changes may involve a high probability that a fire outbreak has recently occurred.

For each input linguistic variable, Table 2 shows its Fuzzy Set (FS) and Fuzzy Domain (FD). According to (1), for every

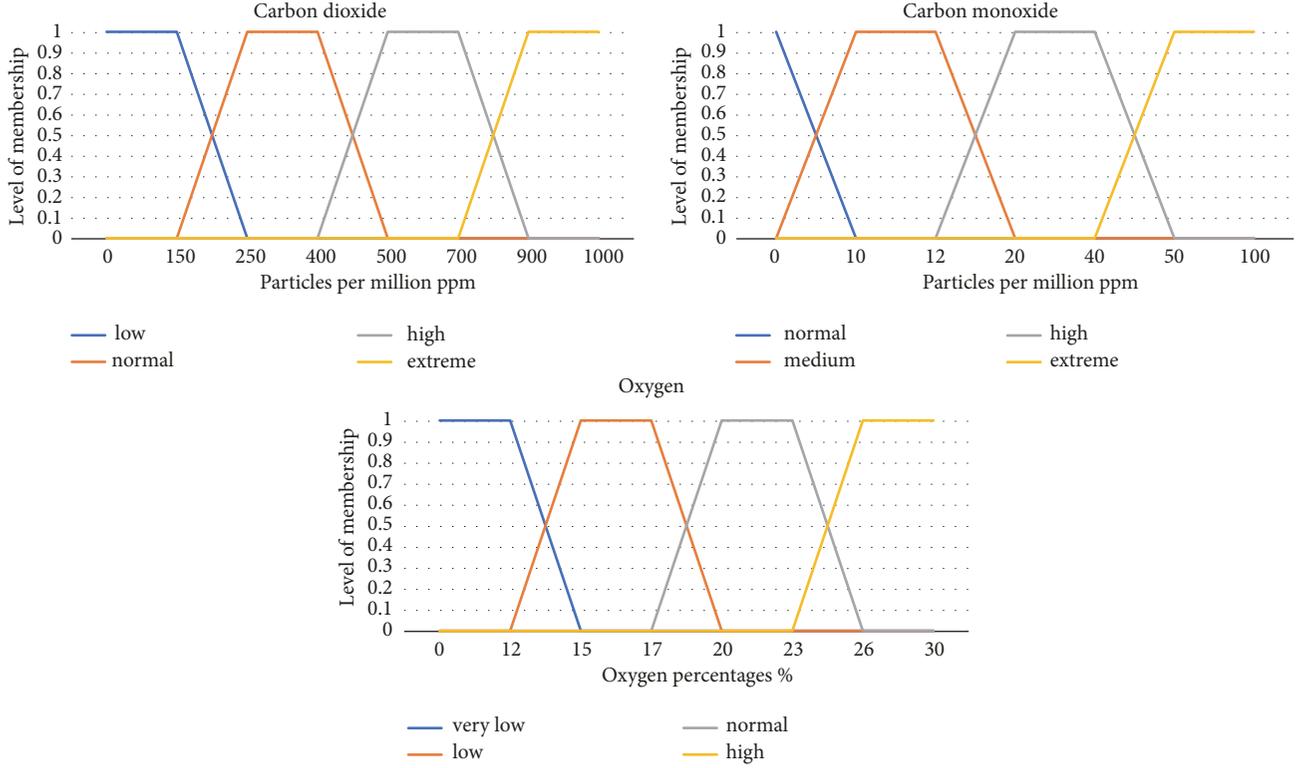


FIGURE 3: Membership functions of polluting gases and oxygen.

TABLE 3: Average computation of monitored dynamic risk factors.

Forest fire risks	Fire outbreak occurrence	Measurement frequency	Average calculation
Non-existent	Non-existent	5 minutes	Last 20 measurements
Low	-	2 minutes	Last 15 measurements
High	-	Without measurement delay	Last 10 measurements
Extreme	Low / High / Extreme	Without measurement delay	Last 5 measurements

ν , an environmental measurement α_ν , of the linguistic variable ν is measured within the considered thresholds $[a, b]$ of its fuzzy domain FD_ν . This value is fuzzified into the corresponding membership function, so its level of membership $\mu_{FS_\nu}(\alpha_\nu)$ is calculated for the i -th fuzzy set proposed for the environmental variable ν (“very low”, “low”, etc.). Calculated levels of membership with respect to all four fuzzy sets proposed for every linguistic variable are added up to obtain a final value of 100%:

$$\forall \nu \in (T, H, W_{speed}, R, O_2, CO_2, CO) \exists \alpha_\nu \in [a, b] \mid \sum_{i=1}^4 \mu_{FS_\nu}(\alpha_\nu) = 100\% \quad (1)$$

Every monitored linguistic variable is analysed by fuzzifying the value of the last measured environmental value and its average. Previous measurements of every dynamic risk factor are used to calculate the average, which is also fuzzified into the membership function of every input linguistic variable aiming at expressing if the average is “normal”, “low”, “high”,

etc. The number of measurements used to calculate the average depends on the analysed environmental conditions with regard to every variable (see Table 3).

3.2. Inference-Rule Evaluation. A knowledge base intended to evaluate unusual environmental changes between the last environmental measurement and the average of each input linguistic variable (previously fuzzified) is here proposed. Unexpected increases of the last fuzzified values of temperature, wind speed, or concentrations of polluting gases with respect to their corresponding fuzzified averages in a particular forest area are analysed. Likewise, unexpected decreases in fuzzified values of relative humidity, precipitation, or oxygen produce the same effect. These environmental events are detected when there is a difference with regard to the fuzzy set with which the last environmental measurement and the average present a greater level of membership. For this purpose, we have used the first neural network model for implementing fuzzy systems, the so-called Fuzzy Associative Memory (FAM) [21]. One FAM has been proposed for each considered linguistic variable (temperature, humidity, carbon

TABLE 4: Inference-rule evaluation for carbon monoxide variable.

Last CO measurement / CO average	normal	medium	high	very high
Normal	NFO	LFO	LFO	LFO
Medium	LFO	LFO	HFO	HFO
High	HFO	HFO	HFO	EFO
Extreme	EFO	EFO	EFO	EFO

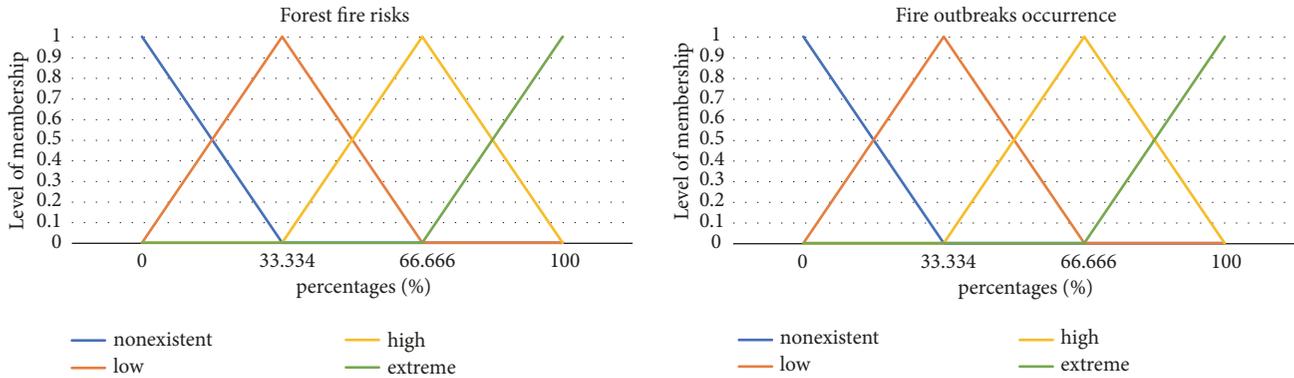


FIGURE 4: Membership functions of output variables.

dioxide, etc.). All of them compose the knowledge base of this fuzzy-based forest fire controller. According to the consulted expert knowledge, the triggers of the rules on the linguistic variables are previously set through appropriate overlaps of the fuzzy sets of input variables. These proposed FAMs evaluate fuzzified input values on the basis of two different objectives:

- (1) **Fire risk prevention module.** Fuzzified values of the last measurement and average corresponding to temperature, relative humidity, wind speed, and rainfall (meteorological variables) are compared with the aim of evaluating the existence and severity of forest fire risks (nonexistent, low, high, and extreme) in every forest area. The objective is to evaluate the probability of considering this forest area as a risk zone to be affected by the beginning of a forest fire. Therefore, the considered output linguistic variable is the existence of forest fire risks.
- (2) **Fire outbreak detection module.** In addition to fuzzified values of meteorological variables, proposed FAMs compare the fuzzified concentrations of carbon dioxide, carbon monoxide, and oxygen in order to evaluate the probability that a fire outbreak may have recently occurred in that forest area (nonexistent, low, high, or extreme). Therefore, the related output linguistic variable corresponds to the probability of detecting a recent fire outbreak. Table 4 shows the proposed FAM for carbon monoxide that analyse the probability of fire outbreak occurrence obtained by comparing their fuzzified values (average and last measurement). For simplicity, the following notation has been used to denote the probability of Fire Outbreak:

nonexistent (NFO), low (LFO), high (HFO), and extreme (EFO).

3.3. Aggregation of Outputs and Defuzzification. Once inference rules have been used to evaluate fuzzified values for both modules (prevention and detection), the results obtained with respect to evaluating every input linguistic variable are aggregated into two different global output sets and fuzzified into the proposed output membership functions. One of the two output sets includes all the results of the inference-rule evaluation corresponding to the existence of fire risks (prevention module). The second one is composed of the results of the inference-rule evaluation with respect to the probability that a recent fire outbreak has occurred (detection module). The percentage highlights the discourse of universe of both output linguistic variables. Thus, all fuzzified outputs obtained from the inference-rule evaluation step are represented in the range of 0-100%.

Figure 4 shows the fuzzy sets proposed for both output linguistic variables: “nonexistent”, “low”, “high”, and “extreme”. The inference rules relate input fuzzified variables with those fuzzy sets through FAMs.

Both obtained output sets are defuzzified through applying the centroid method [22] whose aim is to obtain the gravity center of each output set. On the one hand, a nonfuzzy discrete percentage of the forest fire risks existing in the corresponding forest area is obtained that represents the result required by the prevention module. On the other hand, the probability that a fire outbreak has recently occurred is obtained by applying the aforementioned defuzzification method in the other output set. Finally, the Web service is responsible for activating environmental alerts and notifying emergency corps depending on the estimated forest fire risks

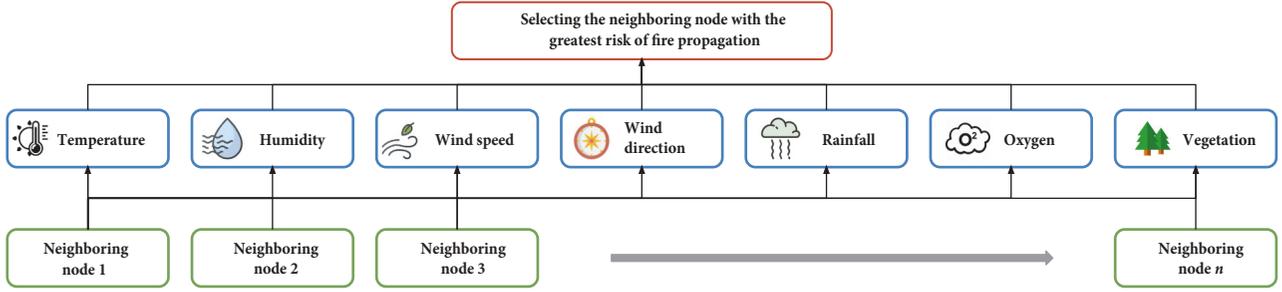


FIGURE 5: Proposed criteria.

TABLE 5: Notation used for analysing fire spread.

Notations	Description
$Node_{fire}$	IoT device located in the forest area where fire was detected
$wind_direction$	Linguistic variable of wind direction
$Loc(n)$	Function that calculates the location of a WSN node n
$Fuzzy_{fire\ spread}(x)$	Fuzzification of location x of a node into $fire\ spread$ membership function

(%) and the obtained evidence of fire outbreaks occurrence (%).

4. AHP-Based Fire Spread Estimator

If the fuzzy-based forest fire controller detects evidences that a fire outbreak has recently occurred in a particular forest area, a decision-making method for analysing the fire propagation is activated. For this purpose, AHP has been used with the aim of evaluating and selecting which neighbouring forest areas are more likely to favour fire spread and to be affected by nearby fire outbreaks as consequence of their environmental conditions. With respect to this, seven criteria have been defined in order to select the best alternative (nearby forest area) as Figure 5 shows.

The values of meteorological variables (such as temperature, relative humidity, rainfall, and wind speed) and the oxygen level have been considered among the seven criteria. For this purpose, fuzzified input values of these measured environmental variables for sensor nodes located in a nearby forest area from where the fire outbreak was recently detected are considered. These sensor nodes are considered neighbours of the affected area. One of them and, in particular, the WSN sensor node located in a neighbouring forest area that is more likely to be affected by the fire outbreak recently detected is selected as the best alternative. These meteorological criteria are relevant because they have a direct impact on the state of existing vegetation or organic fuel, thus favouring fire spread. Required fuzzified environmental values are returned by the Input Variables Fuzzification step of Mamdani's inference, when new environmental data packages (measured by every nearby forest area) are analysed by the proposed fuzzy-forest fire controller.

The wind direction measured in the forest area where the fire outbreak was detected is considered as a main criterion. Every WSN node is capable of measuring this environmental variable in degrees with respect to the North. On the one

hand, each IoT device knows the location in degrees of every neighbouring WSN node with respect to the North. Through comparing their locations and the wind direction, it is determined whether every neighbouring WSN node may be "extremely near", "very near", "near", "moderately near", or "far" with regard to the direction of fire spread that is affected by the current state of wind in that forest area. Table 5 shows the notation used to describe this process.

According to (2), the difference between the location of every neighbouring WSN node and the current wind direction, both measured in degrees to the North, is calculated and fuzzified into the membership function that Figure 6 shows. This membership function has been implemented aiming at calculating the proximity of the node to the fire spread direction. In this example, the difference between the location of the neighbouring node 1 and the last measurement of wind direction registered by the sensor node located in the forest area recently affected by fire outbreaks is fuzzified into this membership function. A value of 100% is obtained with respect to the fuzzy set "extremely near" and 0% for the rest of fuzzy sets. This result involves that the fire spread direction may be extremely near the location of the neighbouring node 1. Fuzzy sets for the wind direction variable have been proposed according to the features of the used sensor.

$$\begin{aligned}
 \forall n \in \{neighbouring\ WSN\ nodes\ of\ Node_{fire}\}, \exists x \\
 \in [0^\circ, 360^\circ] \text{ such that} \\
 x = \min(|Loc(n) - \alpha_{wind_direction}|) \longrightarrow \\
 \exists y \in \{extremely\ near, \text{ very near, near,} \\
 moderately\ near, far\} \mid y = Fuzzy_{fire\ spread}(x)
 \end{aligned} \tag{2}$$

In addition to the hierarchical structure of the proposed criteria, a comparison scale has been implemented to provide different pairwise comparison levels: "equally important"

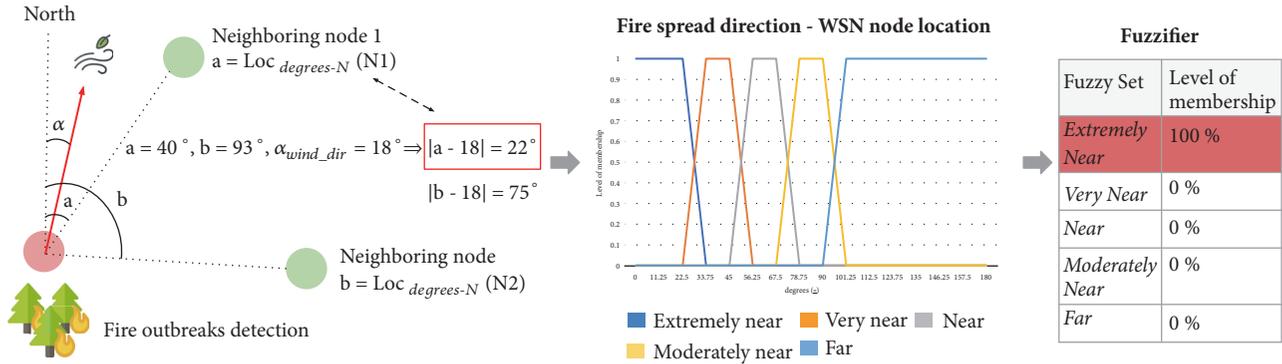


FIGURE 6: Membership function of fire spread direction: WSN node location.

TABLE 6: Matrix pairwise criteria comparison.

Criteria	Temperature	Humidity	Rainfall	O2	Wind _{speed}	Wind _{direction}	Vegetation
Temperature	1/1	1/1	1/1	1/1	1/3	1/5	1/5
Humidity	1/1	1/1	1/1	1/1	1/3	1/5	1/5
Rainfall	1/1	1/1	1/1	1/1	1/3	1/5	1/5
O2	1/1	1/1	1/1	1/1	1/3	1/5	1/5
Wind _{speed}	3/1	3/1	3/1	3/1	1/1	1/3	1/3
Wind _{direction}	5/1	5/1	5/1	5/1	3/1	1/1	1/1
Vegetation	5/1	5/1	5/1	5/1	3/1	1/1	1/1

(referenced as comparison number 1), “moderately more important” (number 3), and “strongly more important” (number 5). Regarding paired-wise comparisons among alternatives according to each criterion, the importance level assigned to every alternative with respect to the others depends on the forest fire risks associated with their fuzzified values.

When two alternatives present the same fuzzy value (such as “high” or “low”) for a given criterion (temperature, humidity, etc.), a comparison level of 1 “equally important” is used. However, when they are not equal, each fuzzy set of difference between both fuzzy values involves one higher level of importance that will be assigned to the sensor node whose fuzzy value may cause more forest fire risks. For example, regarding the membership function and fuzzy sets proposed for temperature (“normal”, “medium”, “high”, and “extreme”), “normal” and “high” fuzzy values of two alternatives or WSN nodes are considered. For this criterion, the second alternative highlights with respect to the first one through a comparison level of “strongly more important” as consequence of existing two fuzzy sets of difference between fuzzy values (medium and high). With respect to this, the second alternative is more likely to favour fire spread as result of its fuzzy temperature value. Thus, the differences with respect to fuzzy sets have a direct impact on the importance level or weight difference assigned to every WSN node.

Regarding criteria comparison, Table 6 shows the weight comparison matrix for the seven criteria.

5. Proposed System

The proposed system is based on a WSN, a Web service, and a mobile application. The WSN is in charge of performing real-time environmental monitoring. The Web service integrates the fuzzy-based fire controller and the AHP-based fire spread estimator aiming at analysing the existence of forest fire risks in every monitored forest area, detecting recent fire outbreaks, and estimating fire propagation. With respect to this, the activation of environmental alerts depending on the results obtained by the proposed fuzzy-based forest fire risk controller and decision-making method is implemented. Through the proposed mobile application, members of the emergency corps are notified. Therefore, the proposed system is responsible for the following:

- (1) Analysing the states and unusual variations of the monitored environmental variables through the proposed distributed WSN.
- (2) Coordinating active and deployed members of emergency corps in areas at risk of forest fires, ensuring their safety and tracking their location at any time.
- (3) Managing efficiently the state and energy of the system resources deployed in the environment, such as the battery level of WSN nodes.

For the coordination of emergency corps, the implemented mobile application allows establishing a real-time communication service with the Web service and the emergency corps headquarters.

5.1. Wireless Sensor Network. The proposed WSN is aimed at implementing an environmental monitoring interface capable of measuring meteorological variables (such as temperature, humidity, wind, and rainfall), polluting gases (such as carbon dioxide and carbon monoxide) and oxygen level. Every WSN node is based on a particular prototype of IoT device that is distributed through different forest areas, composing a distributed WSN.

Regarding the proposed prototype of IoT device, it is based on Arduino platform and mainly composed of a mainboard, seven environmental sensors, and a support board for allowing their integration. Two particular modules are also assembled in order to provide 4G and Wifi communications. On the one hand, the 4G module allows sending the environmental information measured by sensors to the Web service. It also provides a GPS service capable of accessing the location of every IoT device. On the other hand, the Wifi module is aimed at providing Wifi-Direct communications [23] among IoT nodes. The 4G and Wifi modules do not transmit information simultaneously. Wifi-Direct communications are only enabled when a particular sensor node is not able to transmit wirelessly through 4G the recent measured environmental information to the Web service as a consequence of being out of network coverage in that moment. Thus, these communications are intended to provide a multihop-routing protocol among nearby IoT devices aiming at reaching a sensor node with 4G network coverage.

Temperature and humidity are measured by a same digital sensor capable of providing operational ranges between -40°C and $+85^{\circ}\text{C}$ and $0 - 100\%$, respectively. Wind parameters (speed and direction) are measured by an anemometer (with measurement range between 0 and 240 km/h) and a wind vane. In addition, a pluviometer composed of a small bucket for measuring rainfall is assembled. A maximum bucket capacity of 0.28 mm of water is allowed. Pollutant gases are measured by two different sensors. On the one hand, the carbon dioxide measuring range allows the measurement of concentrations up to 10000 ppm with a response time of 60 seconds. On the other hand, the carbon monoxide sensor is able to perform environmental measurements below 1000 ppm (with response time of 1 second). Finally, the oxygen level can be measured between 0 and 30% (with response time of 15 seconds).

The power supply of the IoT device prototype is based on an external rigid solar panel of 7 volts (V) that can provide a maximum charging current of 300 mA, aiming at recharging a connected rechargeable lithium-ion battery. This battery provides 6600 mA x h and a continuous nominal voltage of 3.7 V. To reduce the energy consumption below 33 μA , several sleep modes may be enabled when forest fire risks do not exist in the corresponding forest area. In addition, Web service monitors in real time the current battery level of every sensor node through the last sent environmental measurement.

Once environmental variables are measured, environmental measurements and other device parameters (such as the battery level) are formatted to obtain a new environmental data package. Every dynamic risk factor (temperature, humidity, etc.) is referenced by an alias of a few characters

to decrease the size of the package that will be sent. The proposed environmental data package format is as shown in the following.

$$\begin{aligned} T : \langle value \rangle, H : \langle value \rangle, W_{speed} : \langle value \rangle, W_{direction} : \langle value \rangle, \\ R : \langle value \rangle; \\ O_2 : \langle value \rangle, CO_2 : \langle value \rangle, CO : \langle value \rangle; \\ BatteryLevel : \langle value \rangle, Lat : \langle value \rangle, Lng : \langle value \rangle \end{aligned} \quad (3)$$

Time frequency of environmental measuring can be updated depending on the previously estimation of forest fire risks, detection of recent fire outbreaks, or activation of external forest fire alerts by the emergency corps. Instead of measuring the considered dynamic risk factors every 5 minutes, the sensor nodes located near the affected forest area will measure without any time delay. Likewise, WSN nodes that are neighbours of an IoT device located in a forest area at risk of fire will also increase the frequency of environmental measuring. The Web service is in charge of adjusting the environmental measurement cycle of every WSN node depending on the continuous forest fire risks analysis (shown in Table 3).

5.2. Web Service. Environmental information measured by the WSN is continuously sent to the Web service, which is mainly composed of a server that integrates the proposed fuzzy-based forest fire controller. The Web service is in charge of maintaining an environmental dataset history for every monitored forest area including:

- (1) Every environmental measurement registered by the WSN.
- (2) Average of monitored dynamic risk factors and corresponding coefficient of variation (aimed at analysing its variability and detecting possible errors in values measured by the WSN).
- (3) Results given by the fuzzy-based forest fire controller for each received environmental data package, including short-term forest fire risk estimation and probability that a fire outbreak has recently occurred.

Interactive elements such as linear and bar graphs, visual gauges, and maps are used to represent environmental information. The Web service is also responsible for the activation of environmental alerts depending on results obtained by the fuzzy-based forest fire controller. According to the proposed fuzzy sets of output variables, a colour code has been integrated into every proposed visualization element. "Nonexistent" results provided by the fuzzy-based forest fire controller are displayed with green and "Low", "High", and "Extreme" results with yellow, orange, and red colours, respectively. The aim is to improve the visual interpretation of the severity of estimated forest fire risks and detected fire outbreaks.

The forest fire risks and the probability that a wildfire incident has recently occurred are immediately sent to the involved emergency corps. For this purpose, notifications sent by the Web service are received by the proposed mobile

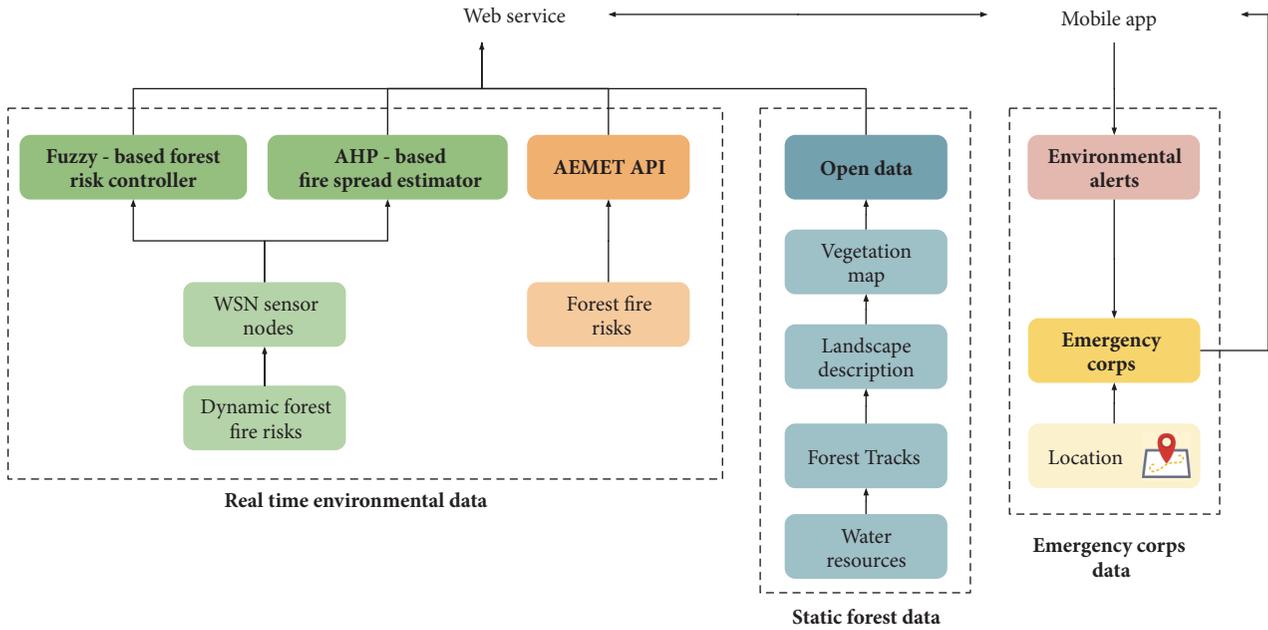


FIGURE 7: Structure of information designed for the system.

application aiming at providing an improvement of the response time of emergency corps. If a fire outbreak in a particular forest area is detected, results given by decision-making method based on AHP are also sent to the involved emergency corps via the mobile application. With respect to this, nearby forest areas with the most propitious environmental conditions to favour fire spread are notified. Finally, a real-time coordination module has been integrated into the Web service and the mobile application to enhance forest fire prevention and fighting operations among the members of emergency corps. Besides, their locations and movements around the affected forest areas are tracked and represented through an interactive map displayed in both the mobile application and the Web service.

Open data sources, like the Spanish Agencia Estatal de Meteorología (AEMET), have also been used to extend the environmental information managed by the Web service and to access certain forest resources that may be relevant to forest fire prevention, detection, and monitoring systems aiming at designing the structure of information of the proposed system (see Figure 7).

6. System Security

The proposal includes different security mechanisms aimed at providing secure communications among WSN nodes, the Web service, and the mobile application. In particular, relevant security requirements for IoT deployment such as data privacy, confidentiality, and integrity together with authenticity have been considered in the implementation.

6.1. Insecurity in WSN Used for Environmental Monitoring. WSN nodes are susceptible to different hazards capable of compromising their integrity, confidentiality, and availability.

When used for environmental monitoring, if WSN nodes are compromised, the fuzzy-based forest fire controller is not able to estimate risks and fire outbreak occurrences, so the response time of emergency corps, losses, and damage caused by forest fires to the ecosystems may be significantly increased.

Communication channels between nodes or between node and Web service may be attacked to get unauthorized access to the environmental information measured by the WSN or to interrupt the transmission of environmental data packages. In addition, environmental data may be manipulated to activate false forest fire alerts, so involving threats to the integrity and confidentiality of data measured by sensor nodes. Once activated, these alerts would reach the implemented mobile application (wrongly notifying the emergency corps). Other manipulation attacks may aim at hiding the existence of fire risks or of the beginning of a forest fire. Besides, data may be also duplicated through forwarding an environmental data package that was previously sent by a WSN node successfully authenticated.

6.2. Implemented Authentication, Signature and Encryption.

An authentication scheme for environmental data packages measured by IoT devices has been implemented through the combination of Lamport's authentication scheme and Lamport-Diffie signature. In particular, a private/public key generation mechanism necessary for the signature of every environmental data package and for the authentication of IoT devices has been implemented following the Lamport's One-Time Password Authentication Scheme.

The procedure based on the Lamport's authentication process is performed as follows. Firstly, every IoT device chooses a secret value w and applies n times a hash cryptography function $H(w)$ on it. The result is a list of n

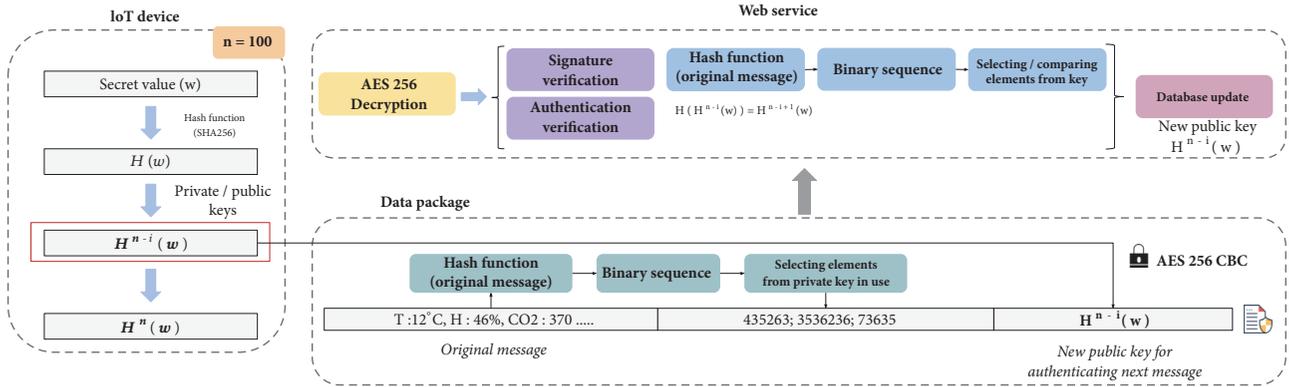


FIGURE 8: Authentication and signature methods proposed for WSN sensor nodes.

one-time private/public key pairs. The last generated key $H^n(w)$ is sent from the corresponding IoT device to the Web service. This key is used as public key for authenticating the first environmental data package sent by the IoT device. For an initial value of $n = 100$ given as an example, the first key sent to the server would be $H^{100}(w)$.

Once the value of n is defined, the IoT device selects the key $H^{n-i}(w)$ for the i -th environmental data package from the list of keys in order to perform its corresponding signature. At this moment, the selected key is considered as a private key and is associated with the key $H^{n-i+1}(w)$ previously stored in the server database. Through the application of the hash function to this private key, the second one (public key) is obtained, so that both compose an authentication key pair according to the Lamport's authentication scheme. For an example with $n = 100$, the key $H^{n-i}(w) \rightarrow H^{100-i}(w) \rightarrow H^{99}(w)$ is selected from the aforementioned key list to sign the content of the first environmental data package. Therefore, keys $H^{n-i}(w)$ (private key) and $H^{n-i+1}(w)$ (public key) compose an authentication key pair for the i -th environmental data package.

After selecting the private key $H^{n-i}(w)$, the IoT device applies the hash function on the content of the new environmental data package to be signed, according to the Lamport-Diffie one-time signature scheme (see Figure 8). This package is mainly composed of environmental measurements and other device data. Then, the obtained result is expressed in a binary sequence, so the bits 0 and 1 are used aiming at selecting the corresponding elements of the private key in use $H^{n-i}(w)$ for the i -th message. Then, the IoT device sends to the server:

- (1) **Signature.** It is composed of the original message (involving the set of registered environmental measurements for each monitored dynamic risk factor and other parameters such as the battery level) and the elements selected from the current private key in use $H^{n-i}(w)$.
- (2) **Private Key in Use.** The key $H^{n-i}(w)$ is used to verify the signature of the package and to authenticate the IoT sensor node in the Web service. If this signature

verification is successful, this key is stored in the server database as the new public key to be used to authenticate the next environmental data package that reaches the Web service.

When the Web service receives a signed environmental data package from an authenticated IoT device, it verifies the attached signature. In order to do it, according to Lamport's authentication scheme, the server checks if the key $H^{n-i}(w)$ obtained in this package is associated with the last public key stored in the database for the i -th message $H^{n-i+1}(w)$. For this purpose, the cryptographic hash function is applied to the first one and the obtained result is compared to the second one, aiming at verifying their match. Regarding an initial value of $n = 100$ and the second environmental package sent to the Web service ($i = 2$), authentication is performed following

$$\begin{aligned}
 H(H^{n-i}(w)) &= H^{n-i+1}(w) \longrightarrow \\
 H(H^{100-2}(w)) &= H^{100-2+1}(w) \longrightarrow \quad (4) \\
 H(H^{98}(w)) &= H^{99}(w)
 \end{aligned}$$

The hash function used in the implementation is SHA-3 (Secure Hash Algorithm 3), which is the latest member of the Secure Hash Algorithm family of standards [24].

Every key available in the list initially generated by the IoT device through the secret chosen value w is considered as a private key or public key depending on its current use. On the one hand, every key is used as a private key to sign an environmental data package. On the other hand, the same key is considered as a public key when it is stored in the database aiming at authenticating the sensor node that has recently sent a new environmental data package to the Web service.

Table 7 shows an example of the signature process and the keys used for the first three environmental data packages registered and sent by the IoT device to the Web service.

Regarding signature verification, the server applies the hash function to the content of the environmental package received from the IoT device. The Web service can deduce which elements of the private key in use should have been

TABLE 7: Authentication for the first three packages.

i -th message	Private key $H^{n-i}(w)$	Public key $H^{n-i+1}(w)$	Authentication
1	$H^{100-1}(w) = H^{99}(w)$	$H^{100-1+1}(w) = H^{100}(w)$	$H(H^{100-1}(w)) = H^{100-1+1}(w)$
2	$H^{100-2}(w) = H^{98}(w)$	$H^{100-2+1}(w) = H^{99}(w)$	$H(H^{100-2}(w)) = H^{100-2+1}(w)$
3	$H^{100-3}(w) = H^{97}(w)$	$H^{100-3+1}(w) = H^{98}(w)$	$H(H^{100-3}(w)) = H^{100-3+1}(w)$

TABLE 8: Environmental dataset defined for estimating forest fire risks.

P	T	H	W_{speed}	R	Av. T	Av. H	Av. W	Av. R
1	41,6	39	55	10	37	46	30	9,5
2	28	57	23	14,7	25	54	25	12
3	22	63,19	7,5	28,83	22,2	64,42	9,5	32,52

TABLE 9: Oxygen level and polluting gases for experimental results.

P	O_2	CO_2	CO	Av. O_2	Av. CO_2	Av. CO
1	16,5	876	47,8	18	592	13,6
2	21	395	10	20	350	7
3	19,1	546	17,61	21,35	454	1,47

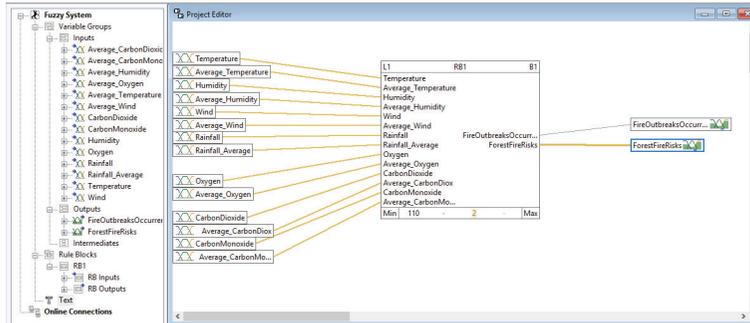


FIGURE 9: Generation of proposed fuzzy-based forest fire controller in fuzzyTECH app.

selected by the IoT device in the signature process. If the signature verification of the i -th message and the node authentication are completed successfully, the server replaces the current public key stored in the database $H^{n-i+1}(w)$ by the new public key $H^{n-i}(w)$ contained in the last environmental data package. This last one will be used during the signature verification process of the next $(i+1)$ -th message, and the IoT device will select the private key $H^{n-i-1}(w)$ for signing a new environmental message.

In the implementation of the proposal, before the transmission of a new environmental package to the Web service, every IoT device encrypts the content of each environmental package through AES block cipher in Cipher Block Chaining (CBC) mode, with keys of 256 bits and zero padding [25]. The use of this algorithm does not involve a significant additional cost of time in the environmental measurements management by the IoT devices. For this purpose, a key predistribution process has been implemented to provide the necessary secret keys based on Lamport's scheme using the hash function.

7. Experimental Results

We have performed an environmental simulation to analyse the results obtained by the proposed fuzzy-based forest fire controller for a particular dataset of environmental measurements. FuzzyTECH application has been used to simulate the proposed fuzzy-based forest fire controller (see Figure 9).

As Table 8 shows, an environmental dataset has been defined aiming at providing the content of three different environmental data packages sent by an IoT device. These packages are referenced as P_1 , P_2 , and P_3 and composed of the last measurement of temperature (T), humidity (H), wind speed (W_{speed}), and rainfall (R). In addition, averages (Av.) of every linguistic variable are included to be analysed. These values are used by the fuzzy-based controller to estimate the existence of forest fire risks (%) in that forest area.

Fire outbreak detection only requires measures of temperature and humidity as meteorological variables.

For every environmental data package, the oxygen level and the concentrations of polluting gases are also measured and included in the dataset, as Table 9 shows.

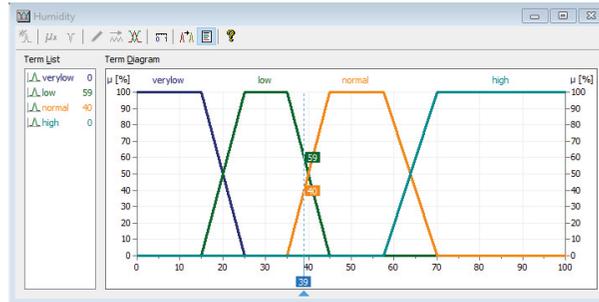


FIGURE 10: Fuzzified humidity values.

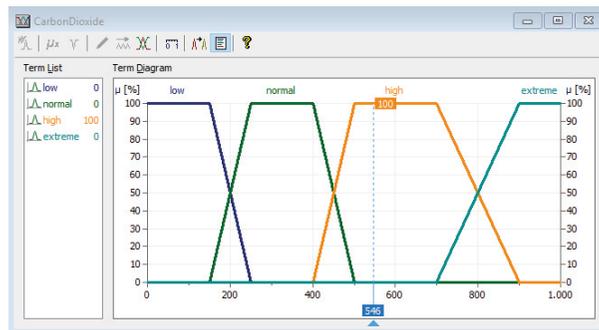


FIGURE 11: Fuzzified carbon dioxide values.

Environmental data package *P1* presents high values of temperature and polluting gases. These environmental conditions may involve a nearby burning process of biomass where the IoT device is located. In fact, both last carbon dioxide and carbon monoxide concentrations indicate a significant increase with respect of their typical average concentrations. In contrast, the last environmental measurement of relative humidity (39%) has decreased with respect to the humidity average (46%). Oxygen level has also decreased from 18 % (average) to 16,5 % (last measurement), so increasing the probability that a recent wildfire incident may be consuming the oxygen in that forest area. On the other hand, packages *P2* and *P3* do not present significant changes between the last measurement and the average of meteorological variables. In addition, measurements of temperature, humidity, and wind speed do not involve “high” forest fire risks due to complying with thresholds proposed by the rule of 30 aforementioned. However, package *P3* presents polluting gases concentrations higher than package 2. Therefore, the result of fire outbreaks occurrence (%) provided by the fuzzy system should be higher with respect to package *P2*.

Discrete values of every environmental package are fuzzified into the corresponding membership function. For example, Figure 10 shows the last measurement of humidity (package *P1*) fuzzified into the proposed humidity membership function. “Low” (59%) and “normal” (40%) fuzzy values are obtained for a humidity discrete value of 39 %.

Figure 11 shows the last measurement of carbon dioxide (package *P3*) fuzzified into the membership function proposed for CO₂.

Thus, the input fuzzification step is applied on every value of the proposed dataset. Table 10 shows all the obtained fuzzy values and their levels of membership. On the left, the last measurements of every variable are fuzzified. On the right, the same process is applied to the averages.

The fuzzified values are evaluated on the basis of the proposed knowledge base and FAMs for every linguistic variable. The aim is to analyse the existence of forest fire risks and fire outbreaks depending on existing unusual changes between the last measurements and the averages that compose the dataset. For every proposed environmental package, Figure 12 shows the result of aggregating all the obtained outputs into the membership function proposed for the output variable related to the existence of forest fire risks.

Outputs related to the probability that a wildfire incident has recently occurred are also aggregated into another output set (see Figure 13). These aggregated outputs are defuzzified by the Centroid method. Regarding the environmental data *P1*, 56,458% has been obtained as the result of the defuzzification process applied to the aggregated output set associated with fire outbreaks occurrence.

Before defuzzification, the output set involved 87% “extreme”, 84% “high”, 59% “low”, and 40% “nonexistent” of probabilities that a wildfire incident may have recently occurred.

Therefore, an unusual increase in polluting gas concentrations and temperature together with the decrease in humidity and oxygen levels show a probability higher than 50% of fire outbreak occurrence. In contrast, 24,074% value has been obtained for *P2* after the defuzzification process.

TABLE 10: Fuzzy values obtained by the fuzzifier.

<i>P</i>	Variable	Value	Fuzzy values	Variable	Value	Fuzzy value
1	<i>T</i>	41,6	High(84%),Extreme (15%)	Av. <i>T</i>	37	High(100%)
	<i>H</i>	39	Low(59%),Normal(40%)	Av. <i>H</i>	46	Normal(100%)
	<i>W_{speed}</i>	55	High(74%), Medium(25%)	Av. <i>W_{speed}</i>	30	Medium(100%)
	<i>R</i>	10	Medium(100%)	Av. <i>R</i>	9,5	Medium(100%)
	<i>O₂</i>	16,5	Low (100%)	Av. <i>O₂</i>	18	Normal(33%),Low(66%)
	<i>CO₂</i>	876	High(12%),Extreme(87%)	Av. <i>CO₂</i>	592	High(100%)
	<i>CO</i>	47,8	Extreme(77%), High(22%)	Av. <i>CO</i>	13,6	Medium(79%),High(20%)
2	<i>T</i>	28	Low(40%), Medium(60%)	Av. <i>T</i>	25	Low(100%)
	<i>H</i>	57	Normal(100%)	Av. <i>H</i>	54	Normal(100%)
	<i>W_{speed}</i>	23	Low(35%),Medium(64%)	Av. <i>W_{speed}</i>	25	Low(24%),Medium(75%)
	<i>R</i>	14,7	Medium(32%),High(67%)	Av. <i>R</i>	12	Medium(100%)
	<i>O₂</i>	21	Normal(100%)	Av. <i>O₂</i>	20	Normal(100%)
	<i>CO₂</i>	395	Normal(100%)	Av. <i>CO₂</i>	350	Normal(100%)
	<i>CO</i>	10	Medium(100%)	Av. <i>CO</i>	7	Medium(69%),Normal(30%)
3	<i>T</i>	22	Low(100%)	Av. <i>T</i>	22,2	Low(100%)
	<i>H</i>	63,19	Normal(54%),High(45%)	Av. <i>H</i>	64,42	Normal(55%),High(44%)
	<i>W_{speed}</i>	7,5	Low(100%)	Av. <i>W_{speed}</i>	9,5	Low(100%)
	<i>R</i>	28,83	High(100%)	Av. <i>R</i>	32,52	High(74%), Extreme(25%)
	<i>O₂</i>	19,1	Normal(69%),Low(30%)	Av. <i>O₂</i>	21,35	Normal(100%)
	<i>CO₂</i>	546	High(100%)	Av. <i>CO₂</i>	454	Normal(46%), High(53%)
	<i>CO</i>	17,61	Medium(29%),High(70%)	Av. <i>CO</i>	1,47	Normal(85%),Medium(14%)

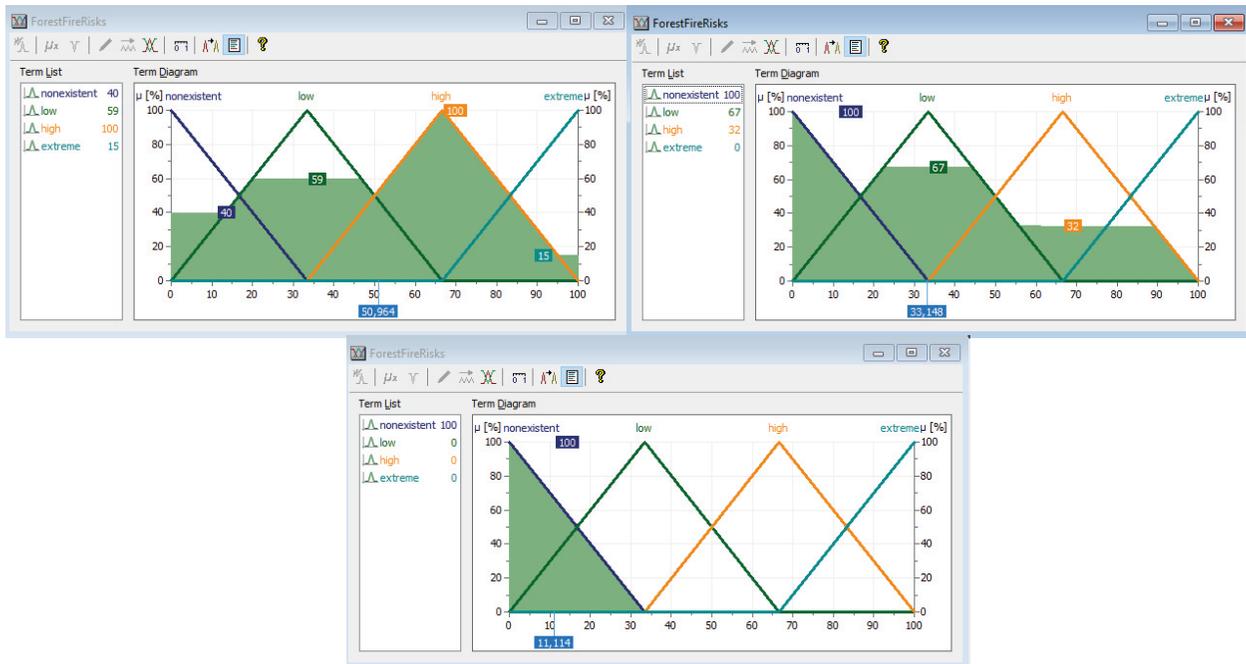


FIGURE 12: Forest fire risks (%) for P1 (top left), P2 (top right) and P3 (bottom middle).

With respect to this, the aggregated output set of P2 involved 100% “nonexistent” and 69% “low” of probabilities with regard to recent wildfire incidents occurrence. Regarding P3, 100% “nonexistent”, 29% “low”, and 70% “high” of probabilities were aggregated for its output set. Although

meteorological variables did not involve significant forest fire risks, in the same way as P2, an unusual increase of polluting gases jointly with decreasing oxygen level involve a higher percentage of fire outbreaks occurrence with regard to P2.

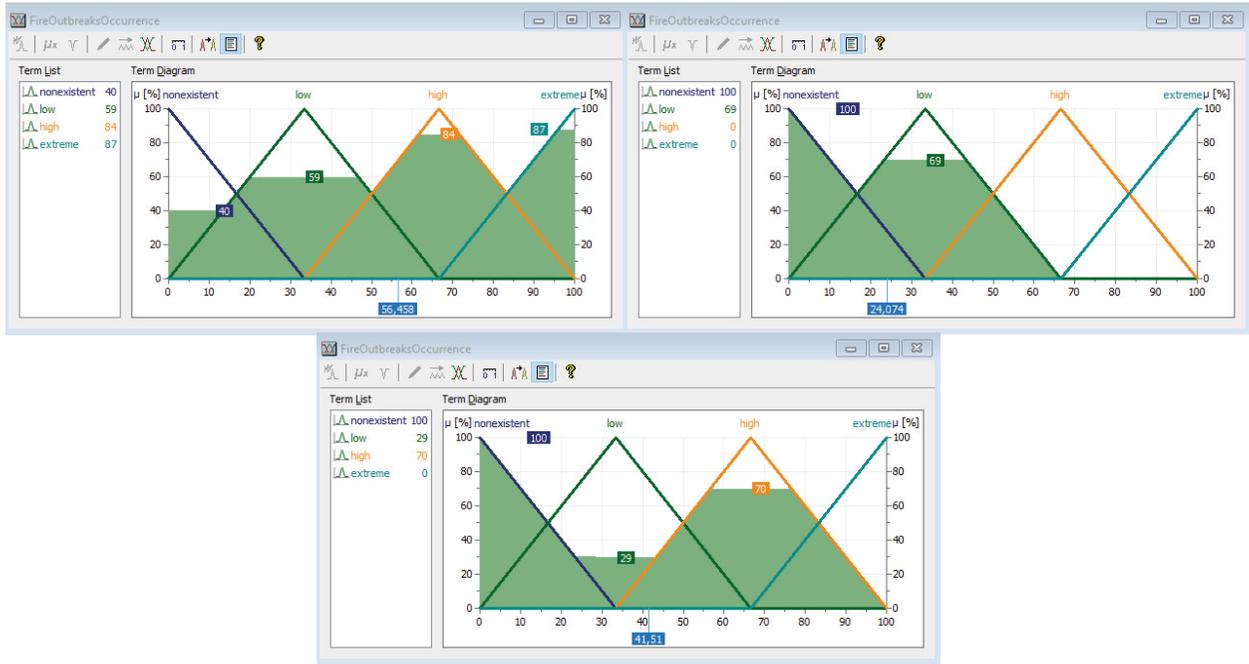


FIGURE 13: Fire outbreak occurrence (%) for P1 (top left), P2 (top right), and P3 (bottom middle).

TABLE 11: Comparison of results provided by fuzzy-based forest fire controller.

P	Forest Fire risks(%)		Fire outbreaks occurrence(%)	
	Defuzzified result	Aggregated output set	Defuzzified result	Aggregated output set
1	50,964%	Non-existent(40%)	56,458%	Non-existent (40%)
		Low(59%)		Low (59%)
		High(100%)		High (84%)
		Extreme(15%)		Extreme (87%)
2	33,148%	Non-existent(100%)	24,074%	Non-existent(100%)
		Low(67%)		Low(69%)
		High(32%)		High(0%)
		Extreme(0%)		Extreme(0%)
3	11,11%	Non-existent(100%)	41,51%	Non-existent(100%)
		Low(0%)		Low(29%)
		High(0%)		High(70%)
		Extreme(0%)		Extreme(0%)

Finally, Table 11 shows an overview of the results provided by the fuzzy-based forest fire controller corresponding to the proposed input environmental dataset. Results of prevention module (forest fire risks) and those of the detection module (evidence of fire outbreak occurrence) may be related in some cases but not in others. With respect to this, a wildfire incident may be caused by malicious attackers even when there are no forest fire risks due to the existence of stable environmental conditions in that forest area. In this case, the result of the detection module may indicate “high” or “extreme” probabilities that a forest fire has begun although the prevention module may indicate “low” or “nonexistent” forest fire risks. This case corresponds to the analysed results of P3 and is the consequence of detecting unusual concentrations of polluting gases.

8. Conclusions and Future Works

This work describes a proposal aimed at performing a short-term estimation of forest fire risks to enhance the response time of emergency corps and existing forest fire prevention, detection, and monitoring systems. In order to do it, real-time environmental monitoring of dynamic forest fire risk factors is carried out through WSNs and novel IoT technologies.

A fuzzy-based forest fire controller has been proposed to analyse measured environmental information, aiming at estimating the existence of forest fire risks, detecting recent wildfire incidents, and activating environmental alerts. Besides, a decision-making method based on AHP has been used to determine nearby forest areas with favourable

environmental conditions to be affected by close fire outbreaks and to favour fire spread.

Those elements have been integrated into a Web service and a mobile application to improve the coordination of emergency corps. Moreover, open data sources have been integrated to provide an additional support and external environmental information of interest, such as weather data, vegetation layers, and other forest resources.

Special attention has been paid to the implementation of security mechanisms to ensure integrity, confidentiality, and authenticity of communications between WSN nodes and between any WSN node and the Web service. For this purpose, an authentication method based on Lamport's authentication scheme and Lamport-Diffie signature has been implemented using SHA-3 hash function, and environmental information has been encrypted through AES 256 in CBC mode.

The proposal described here is part of work in progress. Several open research lines are the introduction of machine learning in the WSN in order to provide an enhancement in the detection of unusual environmental events in every monitored forest area. For this purpose, training environmental datasets generated in controlled environments might favour a dynamic configuration process of the fuzzy sets proposed for every monitored environmental variable and each forest area. Besides, the fuzzy-based forest fire risk controller might be also improved if new sensors are assembled into the proposed IoT devices, so that new variables such as the existence of smoke or the distance to the fire could be measured. Finally, blockchain is currently highlighting as a novel technology that might be used to favour the planning of WSN distribution in order to propose decentralized schemes for authenticating new nodes.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research is supported by the Centre for the Development of Industrial Technology, the Spanish Ministry of Economy and Competitiveness, the Government of the Canary Islands, the CajaCanarias Foundation, and the University of La Laguna, under Grants IDI-20160465, TEC2014-54110-R, TESIS- 2015010106, and DIG02-INSITU.

References

- [1] V. Kumar, A. Jain, and P. Barwal, "Wireless sensor networks: security issues, challenges and solutions," *International Journal of Information and Computation Technology (IJICT)*, vol. 4, no. 8, pp. 859–868, 2014.
- [2] C. Karlof and D. Wagner, "Secure routing in wireless sensor networks: attacks and countermeasures," in *Proceedings of the 1st IEEE International Workshop on Sensor Network Protocols and Applications*, pp. 113–127, IEEE, 2003.
- [3] L. A. Zadeh, "Fuzzy logic—a personal perspective," *Fuzzy Sets and Systems*, vol. 281, pp. 4–20, 2015.
- [4] S. H. Zanakis, A. Solomon, N. Wishart, and S. Dublisch, "Multi-attribute decision making: a simulation comparison of select methods," *European Journal of Operational Research*, vol. 107, no. 3, pp. 507–529, 1998.
- [5] L. Lamport, "Password authentication with insecure communication," *Communications of the ACM*, vol. 24, no. 11, pp. 770–772, 1981.
- [6] M. Naor and M. Yung, "Universal one-way hash functions and their cryptographic applications," in *Proceedings of the Twenty-First Annual ACM Symposium on Theory of Computing*, pp. 33–43, ACM, 1989.
- [7] J. Daemen and V. Rijmen, *The Design of Rijndael: AES-The Advanced Encryption Standard*, Springer Science & Business Media, 2013.
- [8] D. M. N. Rajkumar, M. Sruthi, and D. V. V. Kumar, "IoT based smart system for controlling co2 emission," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 2, no. 2, p. 284, 2017.
- [9] M. Hefeeda and M. Bagheri, "Wireless sensor networks for early detection of forest fires," in *Proceedings of the IEEE International Conference on Mobile Adhoc and Sensor Systems*, pp. 1–6, IEEE, 2007.
- [10] S. Garcia-Jimenez, A. Jurio, M. Pagola, L. De Miguel, E. Barrenechea, and H. Bustince, "Forest fire detection: A fuzzy system approach based on overlap indices," *Applied Soft Computing*, vol. 52, pp. 834–842, 2017.
- [11] M. Maksimović, V. Vujović, B. Perišić, and V. Milošević, "Developing a fuzzy logic based system for monitoring and early detection of residential fire based on thermistor sensors," *Computer Science and Information Systems*, vol. 12, no. 1, pp. 63–89, 2015.
- [12] S. Eskandari, "A new approach for forest fire risk modeling using fuzzy AHP and GIS in Hyrcanian forests of Iran," *Arabian Journal of Geosciences*, vol. 10, no. 8, p. 190, 2017.
- [13] C. Kahraman, U. Cebeci, and Z. Ulukan, "Multi-criteria supplier selection using fuzzy AHP," *Logistics Information Management*, vol. 16, no. 6, pp. 382–394, 2003.
- [14] M. A. Khan and K. Salah, "IoT security: Review, blockchain solutions, and open challenges," *Future Generation Computer Systems*, vol. 82, pp. 395–411, 2018.
- [15] S. D. C. di Vimercati, A. Genovese, G. Livraga, V. Piuri, and F. Scotti, "Privacy and security in environmental monitoring systems: issues and solutions," in *Computer and Information Security Handbook*, pp. 835–853, Elsevier, 2nd edition, 2013.
- [16] A. K. Pathan, H.-W. Lee, and C. S. Hong, "Security in wireless sensor networks: issues and challenges," in *Proceedings of the 8th International Conference Advanced Communication Technology (ICACT '06)*, vol. 2, pp. 1043–1048, IEEE, 2006.
- [17] K. Akkaya and M. Younis, "A survey on routing protocols for wireless sensor networks," *Ad Hoc Networks*, vol. 3, no. 3, pp. 325–349, 2005.
- [18] M. T. Lazarescu, "Design of a WSN platform for long-term environmental monitoring for IoT applications," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 3, no. 1, pp. 45–54, 2013.
- [19] S. Rani and S. H. Ahmed, *Multi-Hop Routing in Wireless Sensor Networks: An Overview, Taxonomy, and Research Challenges*, Springer, 2015.

- [20] E. H. Mamdani, "Application of fuzzy logic to approximate reasoning using linguistic synthesis," in *Proceedings of the Sixth International Symposium on Multiple-Valued Logic*, vol. 26, pp. 196–202, IEEE Computer Society Press, 1976.
- [21] B. Kosko, "Fuzzy associative memories," in *Fuzzy Expert Systems*, 1987.
- [22] T. A. Runkler, "Selection of appropriate defuzzification methods using application specific properties," *IEEE Transactions on Fuzzy Systems*, vol. 5, no. 1, pp. 72–79, 1997.
- [23] C. Funai, C. Tapparello, and W. Heinzelman, "Enabling multi-hop ad hoc networks through WiFi Direct multi-group networking," in *Proceedings of the 2017 International Conference on Computing, Networking and Communications (ICNC '17)*, pp. 491–497, IEEE, 2017.
- [24] M. J. Dworkin, "SHA-3 standard: permutation-based hash and extendable-output functions," Tech. Rep. Federal Inf. Process. Stds. (NIST FIPS)-202, National Institute of Standards and Technology, 2015.
- [25] M. J. Dworkin, "Recommendation for block cipher modes of operation. methods and techniques," Tech. Rep. NIST SP 800-38a, National Institute of Standards and Technology, Gaithersburg MD Computer Security Division, 2001.

