A Wildfire Prediction Based on Fuzzy Inference System for Wireless Sensor Networks

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Abstract. The study of forest fires has been traditionally considered as an important application due to the inherent danger that this entails. This phenomenon takes place in hostile regions of difficult access and large areas. Introduction of new technologies such as Wireless Sensor Networks (WSNs) has allowed us to monitor such areas. In this paper, an intelligent system for fire prediction based on wireless sensor networks is presented. This system obtains the probability of fire and fire behavior in a particular area. This information allows firefighters to obtain escape paths and determine strategies to fight the fire. A firefighter can access this information with a portable device on every node of the network. The system has been evaluated by simulation analysis and its implementation is being done in a real environment.

Keywords: Fuzzy System, Wireless Sensor Networks, Forest Fire, Simulation.

1 Introduction

Usually, a wireless sensor networks is composed of multiple nodes spatially distributed in an area. These nodes obtain information on the environment such as temperature, pressure, humidity or pollutants, and send this information to a base station. A wide variety of applications for such networks often apply some kind of supervision, event detection, tracking or control, among others [1]. In [2] a large-scale deployment of these networks has been used for the supervision of wildlife habitats.

Most applications of sensor networks in forest fires are based on the detection of fires, such as [3] which uses a WSN based on a swarm-inspired system for detecting wildfires. Reference [4] shows an algorithm based on fuzzy logic for detecting events. In this case, the event is fire detection. The nodes are equipped with various sensors such as temperature, humidity, light intensity and carbon monoxide. In [5], a satellite monitoring system with a WSN is used to detect a forest fire. In [6] an implementation scheme of communication oriented WSN and monitoring computer is presented. The work in reference [7] reduces the consumption of the transmission using the information gathered by analyzing the Fire Weather Index (FWI) System. Reference [8] uses data from a WSN in the FARSITE simulator for fire detecting.

Other papers are related to the use of WSN to improve the security on evacuations [9]. Reference [10] deals with the use of WSN to improve the information gathering for firefighters, in order to better perform when extinguishing a fire.

Some other research work is related to the study of fire evolution [11] or also fire prevention [12]. Others do real experiments with WSNs in order to evaluate its robustness against real conditions of a wildfire [13].

Traditionally, most wireless sensor networks are used for monitoring meteorological variables, with the final purpose of detecting the occurrence of fires. Only a few distributed approaches are proposed, like the one in [14], where the remote nodes process information of multiple sensors (temperature and smoke) sending alarm to a base station if a node detects an incident.

However, the scope of these networks can be increased by using distributed processing techniques and computational intelligence. In this paper, we propose a novel system for prediction of fire as well as the prediction its evolution. One advantage of this system is the real time processing of environmental variables, and then the information is available in real time, knowing at all times the current state of forests. Hence, if a fire brigade is currently operating in the area, it can choose the escape route or know which attacking side has to put out the fire.

The proposed system, called ISFPWSN (Intelligent System for Fire Prediction using Wireless Sensor Networks), is based on a distributed processing, that transmits information to neighboring nodes and does not need a base station. Centralized algorithms could be a problem in real situations because with a fire, one or more nodes could be burned, so the path to the base station could disappear.

The purpose of ISFPWSN is evaluating the risk of fire as 95% of wildfires are caused by humans [15]. It is necessary to consider sociological information, not only environmental conditions. Apart from the risk of fire, other goal of ISFPWSN is to offer information about the behavior and evolution of the fire in case of wildfire. It reduces the risk of the people exposed and improves the fire detection because it offers information about secure ways of escape and permits evaluation of a strategy for fire extinguishing.

ISFPWSN is based on computational intelligence algorithms that use fuzzy inference systems. It is because a fuzzy system has many advantages for WSN applications [166], such as its simplicity, which permits execution on devices with limited capabilities, or its ability to manage imprecise and uncertain information. All of these characteristics allow us to obtain a robust system without a high computational load.

The remainder of this paper is organized as follow. Section 2 presents the proposed system ISFPWSN. In Section 3, the simulator developed for testing the system is described. The results are presented in Section 4. Finally, Section 5 contains the concluding remarks and provides a discussion for future works.

2 Proposed System

2.1 Hardware Infrastructure of ISFPWSN

The system is designed to be used in a wireless sensor network, such as the one illustrated in Figure 1. This Figure shows a common network made by anchor nodes, but in this case there is no base station. The portable device, which is carried by qualified personnel, acts as base station, gathering the information of the nodes. A brief description about them is given below.

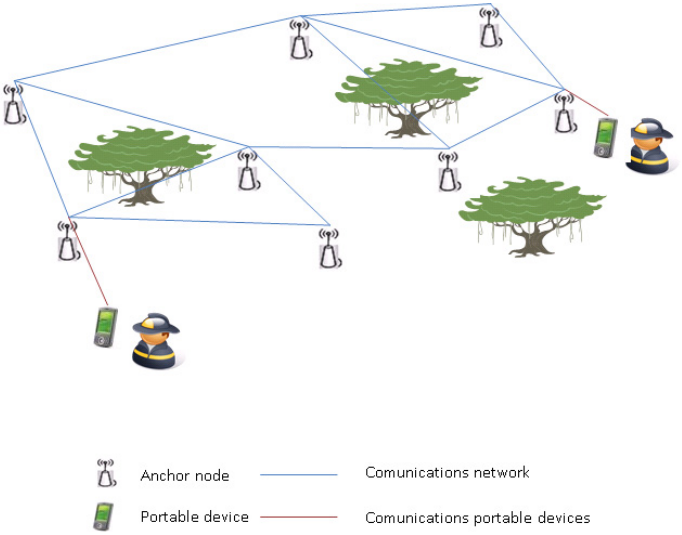

Fig. 1. The ISFPWSN network

Anchor Nodes. Anchor nodes are made up of wireless sensors that form a wireless sensor network. These devices can communicate among each other using the appropriate routing protocols. The nodes execute all the algorithms of ISFPWSN. Every Anchor node obtains the next measurements of sensor which include: temperature, wind direction, wind velocity, daily rain and humidity.

This information can be obtained from a small and cheaper weather station attached to each node, where the node can gather the information through a communication port, such as RS232-C or RS-485. It is interesting to provide power for these systems using renewable energy sources, such as solar panels or wind energy means.

Portable Devices. The other devices used in the project are the measurement apparatus devices. They are small and portable devices used by the fire-fighters to obtain environmental information. These devices can access all information on the state of the fire and can help in case of fire to provide information about its future evolution. This information is useful both to the extenuation and to determine secured ways for an escape; increasing worker safety.

2.2 Descriptions of ISFPWSN Algorithms

The nodes of the network execute their local processing algorithms to obtain the local estimates. Then they send these local estimates to other nodes in the network. Every node of the network gathers its information and executes the distributed processing algorithms. Subsequently, all the nodes share their information about the risk of fire or, in case of a forest fire, its evolution. ISFPWSN does not need a base station to gather the information. This increases the robustness of the network in case of wildfire because if some nodes were damaged in the fire, it is possible that they will not find a route to send the information to the base station.

Figure 2 sums up a flowchart of the main algorithm of the system. This figure shows several processes which will be explained later. In order to save energy, extending the lifetime of the network, the refresh rate (i.e., the frequency at which measurements are taken from the environment and therefore communicating with neighboring nodes), of this algorithm will automatically adjust as a function of the risk of fire. In this approach, each node executes one or other processes depending if a fire has occurred. If there is a fire, it will run algorithms to study their evolution, Fire Behavior (FB) and Prediction of Direction and Velocity of Fire (PD) at the maximum refresh rate. On the contrary, if there is no fire, it will run the prediction process, Probability of Fire (PF) and Risk of Fire (RF).

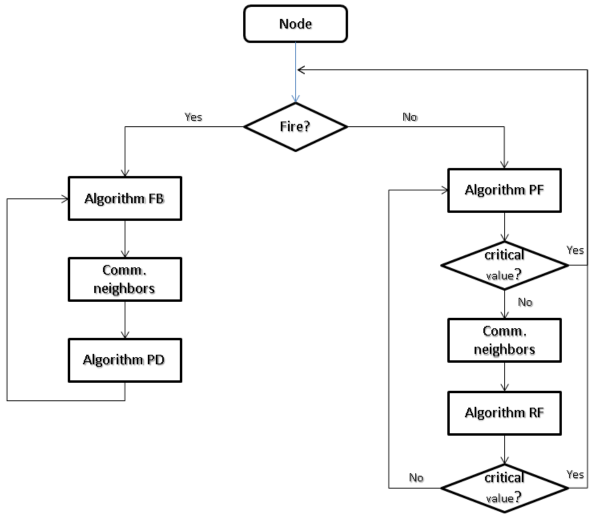

Fig. 2. Flowchart of the main algorithm

If there is a wildfire all nodes are aware and they update their data and communications quickly; obtaining the desired information in the rest of the nodes in real time. In this case, a firefighter can access the data available to the system at any time, and reacts appropriately using the parameters displayed from the nodes in the network.

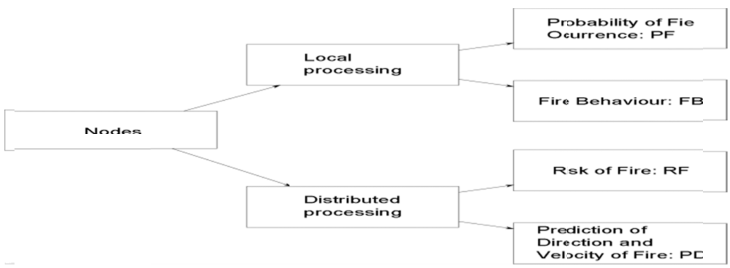

Fig. 3. Processing types

ISFPWSN is based on two main processes: a local process and a distributed process, as shown in Figure 3. These processes shared information between them as well as with the other nodes that form the network.

One goal of our approach is that a firefighter can access this information anywhere on the network, due to the fact that all nodes share information concerning the estimation or the behavior of the fire.

2.3 Local Processing

Local processing is executed on every node of the network. Nodes evaluate the environment with the information provided by each sensor. The local processing offers a partial solution of the global state of the system since this method only uses local information to get the results. This proposed processing is basically a fusion and data aggregation algorithm.

Within local processing there are two algorithms; an algorithm to obtain the probability of fire occurrence (PF) and an algorithm to obtain the behavior of fire (BF).

Probability of Fire Occurrence (PF). This algorithm determines the risk of fire in the environment in the neighborhood of the node.

The output of the PF algorithm is in [0-100] range, which indicates the probability of ignition of a forest fire after normalization. This algorithm is divided up into two blocks: an environmental processing and a sociological processing. Both methods are based on a fuzzy logic engine (Figure 4), and have as outputs fuzzy sets with functions summarized in Table 1.

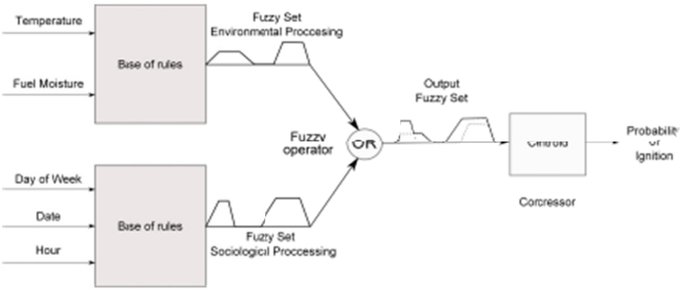

Fig. 4. Algorithm of the probability of fire

Table 1. Fuzzy sets of the outputs of environmental and sociological processing

Name	Membership function
Very low	Trapezoid (-20,0,10,17)
Low	Triangle (13,25,37)
Medium	Triangle (35,47,59)
High	Triangle (57,69,81)
Very high	Trapezoid (79,90,100,120)

Environmental Processing. This processing method obtains the fire likelihood as a function of the environmental variables. This is the classic assumption considered in other fire simulators, such as Behave Plus and FARSITE [17]. These simulators base their approximations on the Rothermel model [18] or the FWI index [19].

To determine the input functions of the fuzzy logic system, a preliminary study of the importance of the climate variables in the generation and evolution of a fire has been done. Therefore, due to historical data of wildfires, temperature and the fuel moisture has been considered as input variables. These magnitudes appear as the most relevant ones.

Fuel moisture is the dead fine fuel moisture. Within it, other variables such as humidity, shading from the sun, slope and terrain exposure has been considered.

The fuzzy sets of the inputs variables are shown in Table 2.

The parameters of fuzzy logic engine have been obtained by ANFIS (Adaptive Neuro Fuzzy Inference Systems) techniques which allows us obtain more accurately membership functions. This fuzzy logic engine has the knowledge base described in Table 3. Because there are 25 rules, this table only shows a small sample sufficient for comprehension.

Table 2. Fuzzy sets of the inputs of the environmental processing

Name	Set	Membership function
Temperature	Very-low	Triangle (-62, -40, -18)
	Low	Triangle (-40, -18, 4)
	Medium	Triangle (-18, 4, 26)
	High	Triangle (4, 26, 48)
	Very-high	Triangle (26, 48, 709
Fuel Moisture	Very-low	Triangle (-5.5, 1, 7.5)
	Low	Triangle(1, 7.5, 14)
	Medium	Triangle (7.5, 14, 20.5)
	High	Triangle (14, 20.5, 27)
	Very-high	Triangle (20.5, 27, 33.5)

Table 3. Base of knowledge of the fuzzy logic engine

Temperature	F. Moisture	Output
Low	High	Very low
Low	Medium	Low
Low	Low	Medium
Medium	High	Low
Medium	Medium	Medium
Medium	Low	High
High	High	Medium
High	Medium	High
High	Low	Very High

Figure 5 shows the probability of fire occurrence. This surface shows the probability for different values of temperature and fuel moisture used in simulations. Temperatures are in [-40 to 49] ºC ranges and fuel of moisture [1 to 27] % range. As it can be seen, when temperature increases and fuel of moisture decreases, the probability of fire occurrence increases, reaching very-high values (around 90-100%).

Sociological Processing. This processing obtains the fire likelihood as a function of the sociological variables, such as weekends or holydays.

As an example, Figure 6 shows the causes of forest fires in Spain during the period 1992-2002. As it can be seen, man causes approximately 95% of wildfires. Moreover, a great percentage of these wildfires are produced during holidays.

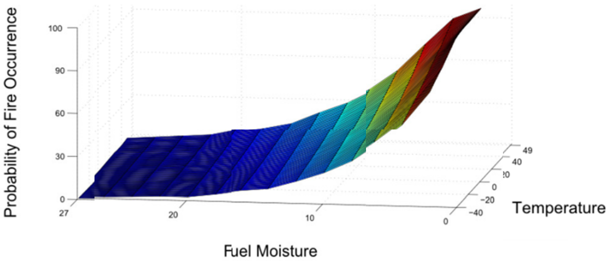

Fig. 5. Probability of fire occurrence

Because of this, it is necessary to consider sociological variables to estimate the risk of fire. As example, we consider that the number of visitor to the natural park is as important as the environmental variables. Despite its importance, fire simulators do generally not consider this kind of information, because it is difficult to assess it.

Sociological behavior is uncertain and it is not easy to model with classic techniques. Fuzzy logic is a good approach to evaluate this kind of behavior. Considering this information is the main objective of sociological processing. It is implemented with a fuzzy logic engine.

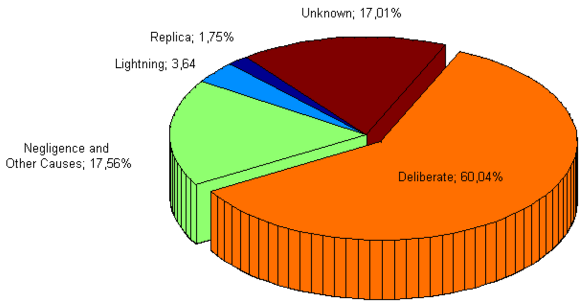

Fig. 6. Causes of wildfires

The input variables are day of week, month and hour time. Its fuzzy sets are summarized in Table 4. These fuzzy sets can be obtained from the past fire information of a region. In this case, we have considered a Spanish report with the information of the fires that took place during the years 1992 – 2002 [15]. Figures 7 and 8 show the fire occurred during this period.

Sixty percent (67%) of forest fires occurred in the months of July, August and September and the time of detection is 73% for fall time slots between 12:00 and 20:00. A low season for park visits is considered between November and April, while the high season considered between June and September. Low visit hours represent times when it is cold during the day (0:00 – 10:00h), while high visit hours are the hours when it is hot during the day (13:00 -19:00h); medium visit hours are all other times. For days of a week, all weekdays were considered low, Saturday or before holidays were considered high and on Sunday or holidays were medium.

Table 4. Fuzzy sets of the inputs of the sociological processing

Hours	Low	0:00-10:00 h.	Triangle
	Medium	10:00-13:00 and 19:00-23:00.h	
	High	13:00-19:00 h	
Months	Very-low	Jan. Feb. Nov.Dec	Triangle
	Low	Mar. Apr.	
	Medium	May. Oct.	
	High	Jun. Sep	
	Very-high	Jul. Aug	
Days of Week	Low	Working day	Gaussian
	Medium	Sunday	
	High	Saturday	

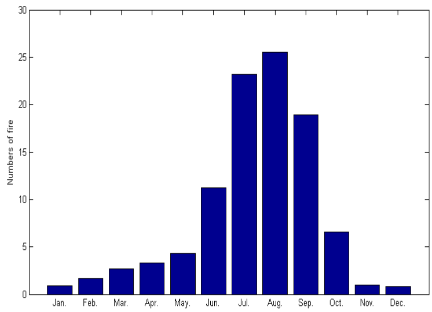

Fig. 7. Month of detection

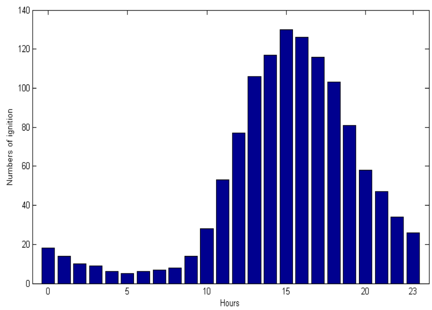

Fig. 8. Detection time

The proposed fuzzy logic engine has 3 input variables; hours, months and days of week and 1 output variable; probability of ignition for sociological variables. This base of knowledge is made up 13 rules. Some of these rules are listed below:

—If hour is Low then Probability of Ignition (PI) is Very-low.
—If months Low then PI is Very-low.
—If hour is Low and month is high then PI is Medium.
—If hour is High and month is Medium then PI is Medium.
—If Day of Week is Medium then PI is High.

Figure 9 shows the different values of the probability of ignition of sociological variables. This area is a surface of probabilities for the input variable hours and months.

It is important to mention that this fuzzy system is designed to apply to Spain, where the dry months are between April and November. For other regions, it would be necessary to change the fuzzy logic engine.

Fire Behavior (FB). This algorithm obtains the direction of the fire front and its velocity in an area around the node. It does not consider the topology of the terrain; it is used on the distributed algorithm for prediction of direction and velocity of the fire.

This algorithm considers the nodes as isolated devices with their local information of wind direction and velocity, temperature, humidity and daily rain. This algorithm is executed only in case of occurrence of fire.

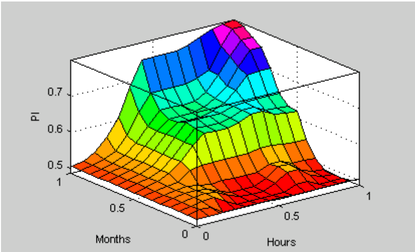

Fig. 9. Probability of ignition for sociological variables

The velocity of propagation of the fire is calculated using the formula below:

$$V = a(U + 1)b \qquad (1)$$

Where V is the velocity of propagation of fire (m/min), U is the wind velocity (m/s), a=0.233 and b=1.332 for a "Pinnus Pinea" forest, as we considered this in this work. The direction of propagation can be obtained as follows.

If wind velocity = 0 Km/h: The fire follows a radial pattern, with the same velocity on all direction.

For other cases, the fire front has the direction of the wind and will trace an ellipse.

This algorithm also implements an alarm system for risk of great fires, according to the rule of 30% [15]. This rule says that a great forest fire can be produced with the conditions described on Table 5.

Table 5. Rule of 30%

Parameter	Value
Temperature	> 30%
Humidity	< 30%
Wind velocity	> 30km/h
Days without rain	> 30

When two or more values are above the threshold, the system considers that there are critical values (Figure2). Instead of taking the system back to the continuous capture of data from the environment, it verifies previously if a fire occurred.

2.4 Distributed Processing

The distributed processing is executed on each node of the network with the information gathered from the broadcast messages sent by the others nodes. This permits checking the global state of the environment without the need for a base station that collects all the information. This is especially useful for the study of wildfire as the route between any nodes to the base station can disappear if any node is burned by the wildfire. Moreover, this allows obtaining the global information, anywhere into the network. It can help firefighters who would only need a small portable device to check the evolution of the wildfire.

The distributed processing scheme combines all the partial solutions from the local processing of the nodes throughout two algorithms: risk of fire and prediction of the direction and the velocity of the fire. These algorithms provide results to assess the overall state of the environment.

Risk of Fire (RF). This algorithm evaluates the global risk of fire in the environment. In this case, it combines the results of every node in the network using the next formula:

$$RF = \frac{\sum_{i=1}^{n} PF_n}{n} \tag{2}$$

Where n is the number of nodes, PF_n is the Probability of Fire of each node and RF represents the risk of fire.

The output of this algorithm is a value [0 to 100] range, which will be encoded in one of five possible risk levels that have been considered. Values above 60 represent a high risk of forest fire; see Table 6.

As described in section 2, the output of this algorithm is the information considered in the refresh rate. This algorithm determines the global characteristic of the wildfire. This information is useful for the firefighters in order to determine the best way to extinguish a fire and the route of escape to be used, which increases the safety aspect of the approach.

Prediction of Direction and Velocity of the Fire (PD). This algorithm determines the global characteristic of the wildfire. This information is useful for the firefighters in order to determine the best way to extinguish a fire and the route to escape to be used, which increases the safety aspect of the approach.

Table 6. Evaluation of the risk of fire

Value RF	Probability of Fire
$RF \leq 10$	Very Low
$10 < RF \leq 30$	Low
$30 < RF \leq 40$	Medium
$40 < RF \leq 60$	High
$RF > 60$	Very High

This algorithm is based on a fuzzy logic system and offers two classes of outputs: the directions of the fire and its velocity.

As appears in Figure 10, the direction of fire is divided into 8 directions (D1 to D8), with 45 degrees between them. D1 represents if the direction of the node with the maximum slope (90º) in relation with a considered node. Every Di variable has two possible values: on or off. On signifies that the fire is going to advance in its direction. Off signifies that fire is not going to advance in its direction.

The velocity of propagation is represented throughout five values: very low, low, medium, high and very high.

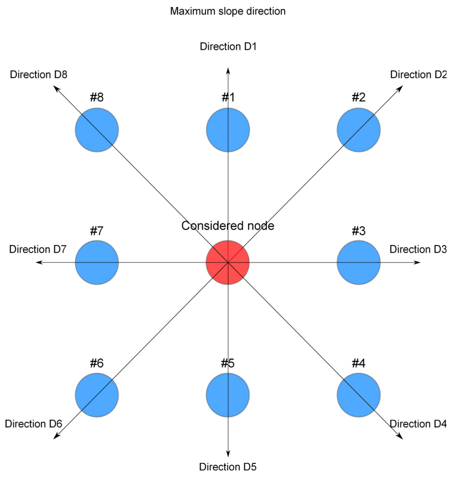

Fig. 10. Considered directions of the fire

As inputs, this algorithm uses the local estimations of the Fire Behavior (FB) algorithm, the speed of the wind and its velocity and the topography of the terrain. The proposed fuzzy logic system is shown on Figure 11.

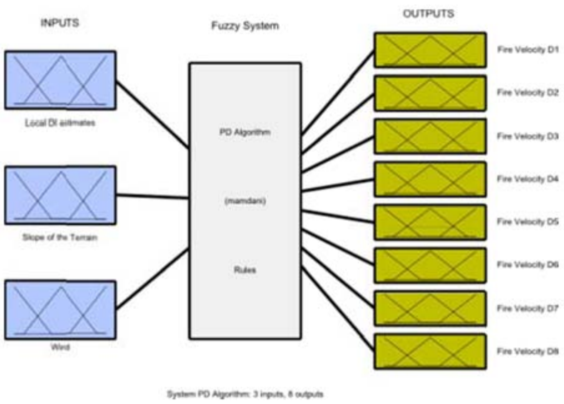

Fig. 11. Representation of the PD algorithm

The fuzzy system uses two internal parameters calculated based on the local estimation of the direction of fire: the consensus direction of fire (DFc) and the consensus velocity of fire (VFc). Both are evaluated as the medium of the local estimations of the system.

Table 7 summarizes the implementation rules. Due to the large number of rules, we only show some of them. All others rules can be obtained along the same lines shown in this table.

Table 7. Rules of PD Algorithms

DFc	VIc	Slope	Outputs
DFc= D1	Low	D1=low	D1, V1 = very low
		D1=medium	D1, V1 = low
		D1=high	D1, V1 = medium
	Medium	D1=low	D1, V1 = low
		D1=medium	D1, V1 = medium
		D1=high	D1, V1 = high
	High	D1=low	D1, V1 = high
		D1=high	D1, V1 = very high
DFc= D4	High	D1=low	D1 = off
		D1=medium	D1, V1 = low
		D1=high	D1, V1 = medium
		D3=low	D3, V3 = low
		D3=medium	D3, V3 = medium
		D3=high	D3, V3 = high
			D4, V4= very high

3 System Simulator

In order to test the proposed algorithms a C++ ad-hoc simulator has been developed. Figure 12 shows a functional diagram of the system architecture. Different Graphical User Interfaces (GUI) are described below.

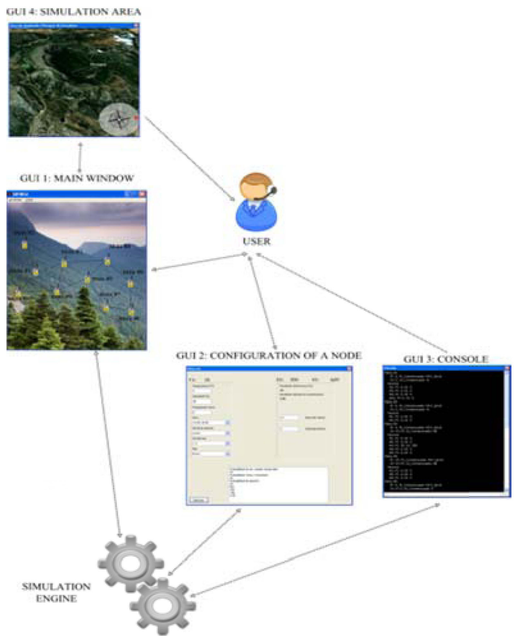

Fig. 12. System architecture

- GUI 1: This is the main window. This GUI shows the distribution of nodes in the environment and the connectivity of each one. This interface is where the user choo-ses the algorithm to perform.
- GUI 2: In this interface, the user can change the configuration of the sensors. This window appears when the user double clicks over a sensor in the main window (GUI 1).
- GUI 3: This is the console. All the partial and global results of the simulations can be obtained in the console window.
- GUI 4: This is the simulation scenario/area. For the first study we have considered localization on the "Pinsapar", a natural park of Grazalema, Cádiz, Spain

This simulator has two classes of inputs: static inputs and dynamic inputs. Static inputs represent characteristic of the terrain and the topology of the network. These variables cannot change on execution time. Dynamic inputs are the measures of the sensors in every node. The information can be changed in the window of configuration of the sensors (GUI 2).

This simulator shows a graphic representation of the risk of fire (Figure 13) and the direction of fire (Figure 14).

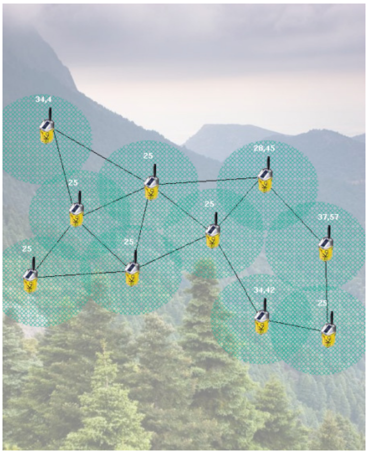

Fig. 13. Representation of the risk of fire

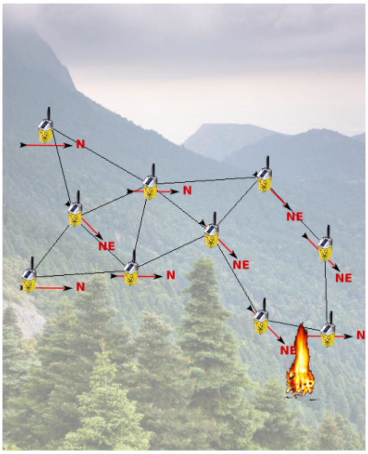

Fig. 14. Representation of the direction of a fire

With this simulator, ISFPWSN algorithm has been verified. In all of the simulated scenarios, ISFPWSN offers a correct response. Its response is similar to that obtained by BehavePlus simulator using the same inputs.

4 Results

To test our system, it has been compared with the results obtained from the Behave Plus Simulator. In Figures 15 and 16, we check the similarity of the probability of fire obtained through our system as well as the probability of ignition obtained by the Simulator Behave respectively. Both figures show the probability as a function of temperature [40 to 49]ºC and fuel moisture [1 to 27]%. Tables 8 and 9 show a brief summary of the information reflected in these figures. They show the values of the probability of ignition with ISFPWSN and the probability calculated with Behave simulator, for temperatures between 20-30ºC and fuel moisture values 1-27%.

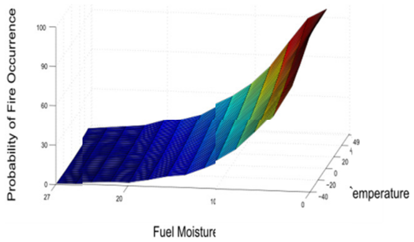

Fig. 15. PI our system

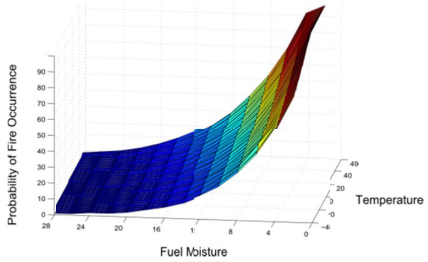

Fig. 16. PI behave plus

Table 8. Probability of ignition, ISFPWSN

Temp/F.Moisture	20	22	24	26	28	30
1	100,154494	100,181871	100,1669	100,111936	100,198908	100,281496
3	80,1878456	80,9286738	81,6457107	82,3462467	83,3241299	84,3033896
5	60,5096055	61,3377787	62,1608225	62,9909075	64,0302917	65,0768419
7	45,2412002	45,9520141	46,6763205	47,4311174	48,1266698	48,8351635
9	33,6203125	34,1887625	34,7703746	35,3870143	35,9384252	36,5022355
11	24,4977716	24,9673453	25,4434935	25,952969	26,4805139	27,0178309
13	18,0825517	18,484547	18,8865327	19,3201445	19,8108575	20,3087161
15	12,37531	12,6156812	12,8562432	13,1335065	13,4524117	13,7775382
17	8,76267436	9,00411181	9,25271814	9,54987376	9,83493396	10,1269967
19	6,07831408	6,31704863	6,56993062	6,8832077	7,10697667	7,33852943
21	3,60197221	3,7504699	3,91668668	4,15173726	4,23018887	4,31962861
23	2,3919787	2,50390544	2,62689982	2,81694903	2,8504334	2,9053503
25	1,51162377	1,59762167	1,68803563	1,84372173	1,80011255	1,78838043
27	0,96091963	1,03163123	1,10010715	1,23206876	1,07923855	0,96873003

To check the accuracy of our system, we calculated the absolute errors (ε). This error is calculated for each pair of values temperature-fuel moisture between the output of our system (PI_{IFPWSN}) and the Behave Simulator (PI_{Behave}). Table 10 shows a subset of these errors for certain values of temperature and fuel moisture.

$$\varepsilon = \text{error} = |PI_{IFPWSN} - PI_{Behave}|$$

As shown in Table 10, the values of the errors are very close to 0. This means that our system is quite reliable. The errors of the system can be summarized as:

- Maximum error = 1.8317 (For the 48ºC temperature and 3% fuel moisture)
- Minimum error = 0.0119 (For the 48ºC temperature and 17% fuel moisture)
- Average error = 0.3588

Table 9. Probability of ignition, Behave Plus

Temp/F.Moisture	20	22	24	26	28	30
1	100	100	100	100	100	100
3	80	81	82	83	84	85
5	60	61	62	63	64	65
7	45	46	47	47	48	49
9	34	34	35	35	36	37
11	25	25	26	26	27	27
13	18	18	19	19	19	20
15	13	13	13	14	14	14
17	9	9	9	10	10	10
19	6	6	6	6	7	7
21	4	4	4	4	4	5
23	2	2	3	3	3	3
25	1	1	2	2	2	2
27	1	1	1	1	1	1

Table 10. Absolute error

Temp/F.Moisture	20	22	24	26	28	30
1	0,1544943	0,1818710	0,1668996	0,1119361	0,1989078	0,2814956
3	0,1878456	0,0713262	0,3542893	0,6537533	0,6758701	0,6966104
5	0,5096054	0,3377786	0,1608225	0,0090925	0,0302916	0,0768419
7	0,2412001	0,0479858	0,3236794	0,4311173	0,1266697	0,1648365
9	0,3796875	0,1887624	0,2296254	0,3870142	0,0615748	0,4977644
11	0,5022284	0,0326547	0,5565065	0,0470310	0,5194860	0,0178308
13	0,0825516	0,4845469	0,1134672	0,3201445	0,8108574	0,3087161
15	0,6246899	0,3843188	0,1437568	0,8664935	0,5475882	0,2224618
17	0,2373256	0,0041118	0,2527181	0,4501262	0,1650660	0,1269967
19	0,0783140	0,3170486	0,5699306	0,8832077	0,1069766	0,3385294
21	0,3980277	0,2495301	0,0833133	0,1517372	0,2301888	0,6803713
23	0,3919787	0,5039054	0,3731001	0,1830509	0,1495666	0,0946497
25	0,5116237	0,5976216	0,3119643	0,1562782	0,1998874	0,2116195
27	0,0390803	0,0316312	0,1001071	0,2320687	0,0792385	0,0312699

Expanding the selection of temperatures throughout the range used [-40 to 49] ºC, the error obtained for each pair (temperature-fuel moisture) are shown is Figure 17 and Figure 18. Figure 17 shows the histogram error; with higher values it is around “0” and it decrease as we move away from the center. Figure 18 shows a three-dimensional view of the error for each pair of temperature-fuel moisture used in the simulations.

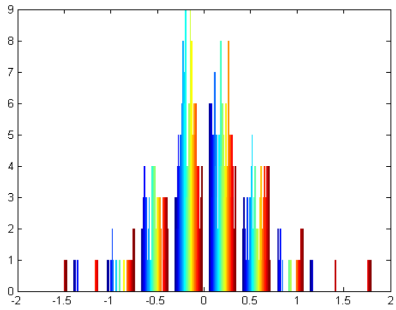

Fig. 17. Histogram error

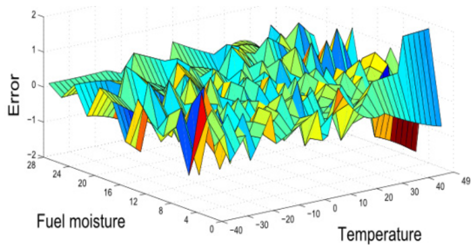

Fig. 18. Dimensional error

5 Conclusions and Future Work

In this work, our ISFPWSN system is presented. This system is based on wireless sensor networks. In order to obtain the probability of fire and fire behavior prediction we use computational intelligence schemes in each of the nodes that belong to the network. One aim of the proposed wireless sensor networks is to be economical, permitting the development of the system in a huge area with a low cost.

The proposed algorithms employ collaborative processing techniques in order to cooperate with the wildfire fighting based on fuzzy logic processing. This system can act in two ways: first, it can determinate the risk of fire and, in such a case, this network gives useful information to the firefighters.

In case of fire, the system gives information about the location and direction of the fire fronts. This information can be used to study in an effective way how to control the fire and how to design escape routes in order to enhance workers' safety.

The results obtained with the proposed system have been compared with the outputs from the Behave simulator, which proved the accuracy of our system.

Currently, we are designing a real prototype version of the system, to be developed in a real environment in order to validate the proposed algorithms. The authors are currently working to develop neural network system to verify the fire behavior algorithms proposed in our scheme.

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