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Event Classification and Intensity Discrimination for Forest Fire Inference With IoT

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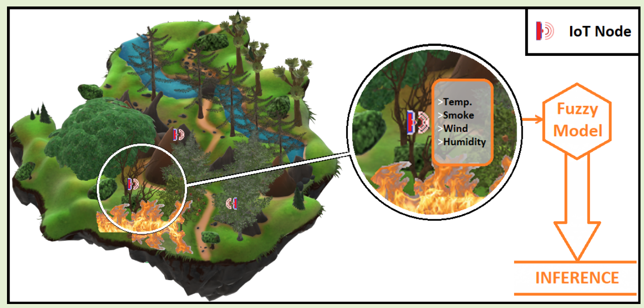
***Abstract*—Simultaneously occurring random events are often reported by multiple nodes. However, the accuracy of the event detection at every node is dependent on the node's relative position from the event, and hence, not reliable. Moreover, the factors influencing the event inference are so many, that the accuracy of such an event detection is compromised. Targeting the problem of accurate event inference in the detection of priority events, such as forest fire, a fuzzy rule-based method is proposed. Four parameters are identified for which fuzzyfied values are obtained by a membership function for every variable. A set of 256 rules are used to generate different permutations of the fire index with respect to the identified variables. Extensive analysis of the results proves the efficacy of the proposed scheme with a significantly reduced error rate of 2.01% for humidity and an error rate of 1.94% for temperature.**



***Index Terms*— Data gathering, energy efficiency, event classification, inference, intensity discrimination, IoT, knowledge extraction.**

I. Introduction

APPLICATIONS such as event detection [1], forest fire detection [2], surveillance systems [3], [4], localization of oil leakages [5] etc. with multimedia wireless sensor networks (WSNs) and/or Internet of Things (IoT), are primarily driven by accurate event inference. However, accuracy in such a scenario is difficult to achieve, because of the following two reasons:

A. Data Redundancy

In practical scenarios, multiple events happen simultaneously, which result in a huge volume of data at the reporting node. This huge volume of data contains event from different sources that need to be processed and classified before any inference can be made. To understand clearly, consider the case where sensor nodes are tasked with reporting the sounds of different animals in an identified area of a forest region. At any moment of time, every node might report multiple events, however, the nodes fail to discriminate the sound generated by different animals. As a result, the reported signal might contain samples from multiple animals and some noise as well but is reported as a single sound signal. This problem of event classification in WSN and IoT networks is known as the problem of mixed sound event verification and is addressed as the first part of the problem statement of this work.

B. Unreliable Inference

The second and less researched reason is that the accuracy of the event detection at every node is dependent on the node's relative position from the event, and hence, not reliable. Considering a different example i.e. of a fire in a forest, where the intensity of the event (in this case forest fire) is different for different sensor nodes and is dependent on the location of the node itself. Intuitively, the nodes closer to the event have the best observation, while the nodes placed far away from the event monitor the event with reduced intensity. Understandably, if the sensing range (R_S) of the nodes is 30 meters (m) and the distance of two nodes from the same event is 2 m and 25 m respectively. Then, all the nodes, for which the event is within the sensing range, can sense and report. However, the node at 2 m distance from the event might report the probability of forest fire to be x and the node at 25 m distance from the event might report the same event with a probability of as y such that $x \neq y$.

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Therefore, the veracity of the event reporting, in such cases, is compromised and results in capricious inference from the observed data. Considering that many practical applications of WSN and IoT, are driven by multimodal signals, i.e. audio, video, images etc. the research in the area of multimodal event detection and inference has led to some very interesting findings and algorithms. To refer to a prominent work, the authors in [6], aims at tracking the speakers, in a closed, crowded and covered environment with the help of audio and visual signals. Yet another work in [7] uses multimodal sensor data for behaviour recognition in human beings. The authors use images, acceleration and sound signals as a means to reach the desired objective. In many of the similar works, such as [8]–[10] and many more, multimodal data was used for detection of incidents in assisted living facilities, traffic management and monitoring and reporting of elderly people at home, respectively. Some other considerable works are those presented in [11], [12] where sound sensors are used to facilitate hearing-impaired persons. In addition to these, a motivated research survey, [13] presents a cogent analysis of the works done in multimodal event discrimination and inference. A careful review of the literature shows that the recent advances in event detection have favourably considered the problem of event discrimination. For instance, the blind source separation (BSS) technique, has been widely used and perfected by optimization over the years [14], [15]. Comparing three topologies of WSNs, the authors in [16], [17], were able to provide some significant insights on the BSS algorithms.

Interestingly, recent years have seen the domination of methods developed by the amulgmation of various technologies such as machine learning (ML), Fuzzy Logic and others. For example, the authors in [18] successfully attempted to train a multiple-metric algorithm a distinct set of metrics, not necessarily homogeneous or heterogeneous, with the aim of accurate classification of events. Another interesting work based on ML is proposed in [19], where the collaborative computing framework and multimodal data fusion are used in body area networks for monitoring human emotion. The studies proposed and discussed in [20], [21] and [22] are some of the major additions to the applications, where ML algorithms have been proved useful in analyzing multimodal sensor data. An interesting approach towards, improving the performance of sensor-based multiresident activity recognition is proposed in [23] using a hybrid fuzzy c-means method (FCM). The idea is to obtain a combination of FCM and change point detection (CPD) for improving the overall performance of classification and segmentation process. Another, recently proposed, fuzzy based approach to address the issue of event classification is the approach proposed in [24] where the event evaluation and actor selection is defined by a fuzzy rule based systems. The scheme, addresses an issue very similar to the one proposed in this work. Therefore, taking a hint from the recently proposed fuzzy methods, this work aims to address the issue of intensity discrimination and accurate event detection by proposing a fuzzy rule based method. The novel contributions of the proposed work are summarized as follows:

1) A fuzzy event classification algorithm.
2) A method to accurately discriminate the event intensities on the basis of relative node positions and the actual event.
3) A mathematical formulation to prove the efficacy of the proposed method.
4) A mathematical formulation to standardize the event intensity vs distance relationship.

The organization of the paper is as follows: in the section II, the problem is defined followed by the system prerequisites in the section III. The section IV presents the proposed solution and the metrics for evaluating the performance of the proposed methodology is given in section V. The results are shown the section VI with the concluding comments in section VII.

II. Problem Description

Multiple simultaneously occurring events, impose severe restrictions on the accuracy of the detection process, as the reported data must be precisely processed and accurately classified for the inference process to be accurate. Failing accurate classification, the reported signal might contain samples from multiple sources and some noise as well but is reported as a single sound signal. This problem of event classification in WSN and IoT networks is popularly termed as a “mixed sound event verification problem” and is addressed in this work. Additionally, it is important to note that the accuracy of the event detection at every node is dependent on the node’s relative position from the event, and hence, not reliable. Intuitively, the nodes closer to the event have the best observation, while the nodes placed far away from the event monitor the event with reduced intensity.

Considering the special case of forest fires, the problem of event intensity discrimination is considered in this work. As explained above, the event (in this case ‘forest fire’) is sensed and reported by a randomly deployed network. However, depending upon the nodes relative position from the event, the intensity of the same event, may be reported differently by different nodes.

Mathematically, the thermal radiation of the fire flames, can be modelled using the point source radiation model [25], which considers a point source to be present at the center of the flame and its distance from the target (in this case ‘nodes’). The relation, as considered by the point source model, is given by:

$$R_{hf} = \frac{\chi\beta}{4\pi d^2} \tag{1}$$

where, the radiant heat flux in kW/m^2, is represented by R_{hf}, the χ gives the percentage of total radiated energy, β represents the rate of heat release in kW and the distance, in (m), between the point source and the target is given by d. It must be noted that ‘$\chi\beta$’ together represent the fire strength.

An alternate approach to model the fire intensity is driven by the solid flame model [26], which works on the fundamental assumption that a simple geometrical shame may be used to represent the fire and that the radiation is only emitted from the fire’s surface.

III. System Prerequisites

A. Event Description and Multimodal Data

The nodes are deployed to detect fire in a forest region. Considering the rough terrain, four parameters were considered in this work: Temperature, Smoke (CO_2, NO_2), Wind Speed and Humidity which have been widely used for early fire detection in outdoor environment. Although, several other factors such as wind direction, fuel content in leaves etc, contribute to the detection of forest fires, but, as suggested in the literature [27], the chosen parameters have been found sufficient to accurately predict and classify the forest fires. All the other reported parameters were considered as noise and were discarded. A microphone array, mounted on the top of each sensor node, is used for communicating the mixed signals to the base station and consequently to the sink where the events are classified and discriminated against based on the reported intensity. The simulation and experimental data are designed/processed with the idea that in case of a single event i.e. one of the four events is reported, the component corresponding to the event is reported as 1 while the remaining components are marked 0. Similarly, if multiple events are reported, corresponding components are marked 1 and 0 otherwise. The proposed model takes y as the input signal which has four components such that every component corresponds to a type of event which such as Temperature, Smoke (CO_2, NO_2), Wind Speed and Humidity in a forest region, respectively. Thus, the data (x_i, y_i) can be explained as following: x_i being the i^{th} sensor reading from the event when the i^{th} fragment is chosen, y_i is the corresponding data label vector and i ranges from 1 to the total number of fragments.

B. Network Assumptions

The study, in the proposed work, assumes the network to be densely deployed with the following:

- 'n' randomly deployed nodes in a forest area of 'S' m^2.
- The relation between the communication range (R_C) and the sensing range (R_S) of the deployed nodes is given by $R_C = 2R_S$ and is considered to be constant for the entire experiment.
- It is assumed that the nodes within the communication range are able to communicate.
- All the nodes are aware of their neighbors and sensing area.
- Owing to the special case of forest fires, a significantly harsh terrain (limited sensing range, frequent node and link loss, limited line of sight, noise due to animal presence etc.) is considered for the experimental and simulation study.

The network assumptions depict a straightforward randomly deployed sensor-based IoT network in an outdoor setting and is fully realizable.

IV. Proposed Solution

Environmental parameters such as temperature, smoke density, wind speed and humidity level are the fundamental units of the proposed model. The model is developed with the aim of accurately detecting the forest fire (preferably in its earliest stage). The idea is to enhance the accuracy of such a system by event intensity discrimination thereby improving the inference. To realize the aim, a fuzzy event intensity discrimination based forest fire detection method is proposed which provides the probability of occurrence of forest fire (based on the environmental conditions) and also the probability that a forest fire has already erupted in the area. The environmental parameters, driving the prediction of fire, might be many. For instance, a combination of high temperature, low humidity and high wind speed may result in a high probability of a possible fire. Similarly, the detection of an already erupted fire may be obtained by a combination of high temperature, high smoke density and high wind speed.

The network is setup in the region of interest. Considering that the detection of fire, at initial stage, is difficult because of the limited sensing range of the sensor nodes, the event intensity mechanism is proposed to determine the relative parameter values of locations where sensor nodes are not present.

Various combinations of parameters, are used to generate fuzzy sets resulting in outcomes in terms of 'low', 'medium', 'high' and 'extreme'. Specifically, temperature, smoke density, wind speed and humidity level are considered for determining the fuzzy rules. The fuzzyfied values are considered as an input for the proposed detection and prediction model.

A. Event Intensity Discrimination

In this section, intensity of parameters are computed at different area of the interest where sensor nodes are deployed. In this four parameters are considered that are temperature, smoke, wind speed and humidity level. The intensity of the parameters are calculated on the basis of the values that are measured by the sensor node.

1) Temperature: Temperature intensity at distance d is computed using solid flame radiation model [26]. As per the aforementioned model, a simple geometrical shape may be used to represent the solid body and it is assumed that the surface emits thermal radiation. The model also assumes that the radiation from non-visible gases, is minimum. The volume of the fire has an important consideration as there might be case when the entire volume of the flame is not in direct line of sight of the target. Mathematically, it is important to note that radiation intensity, as observed from the fire pool, to elements lying outside the envelope of the flame such that the wind intensity is extremely low and hence considered "no wind", has the following relation [26]:

$$R_f = \varepsilon \times \sigma \times T^4 \times C_f \tag{2}$$

where R_f is the incident radiative heat flux (kW/m^2), the flame emissivity is given by ε and σ represents the Stefan-Boltzmann constant whose standard value is $5.67 \times 10^{(-11)}(kW/m^2K^4)$. The temperature of the fire (T) in K and C_f is used as the the view factor and ranges between 0 and 1.

It is empirical to mention that the equation 2 is calculated assuming the no component of the emitted radiation is absorbed by the air (water vapour, carbon dioxide etc.). This assumption allows the calculations suited for worst case analysis of the radiation intensity.

To clarify, the view factor, is the amount of radiation emitted from one surface that impacts another surface directly. Consider a hemispherical surface which is visible from the hemisphere, the view factor as such is the portion of this hemispherical surface as seen by one of the many differential elements, such that the angle of view is considered from a different element also present in the same hemisphere. The view factor, thus obtained, is a mathematical function derived from the location of the target, height of the fire flame, and the width of the fire. It thus becomes quite straightforward to interpret that the values tends to reach 1 as the distance between the target and the flame is minimised. Additionally, the width of the fire alternatively termed as the flame diameter, is given by D and that the height of the flame is given by F_h. In case, when the fire pool has a length-to-width ratio of 1, a source, with an equivalent circular area, is considered for obtaining the flame length and may be obtained by the following relation [28]:

$$F_h = 0.235 \times H_{rr}^{\frac{2}{5}} - 1.02 \times D \tag{3}$$

such that F_h is in m, rate of heat release is measured in kW and is given by H_{rr}. The width of the burning region is given by D and is measured in m. The H_{rr} may be obtained on a case to case basis based on the experimental setting. For the purpose of this study in the absence of experimental data, the maximum HRR for the fire.

Several factors contribute to the values of radiation exchange which happens between the original fire source and the receiving element outside the fire flame. These factors include the F_h, D, H_{rr} and the specific properties of the receiving element [26]. The practical implementation of the system requires that a vertical cylindrical structure to be used to approximate a turbulent diffusion given that the environment is wind free. Depending upon the position of the target (on ground or at elevated level equivalent to fire flame), a single geometrical structure is sufficient to approximate the flame structure. However, in cases where the target element is at elevated level, more than one cylindrical structures may be required for accurate approximation. Fig. 1 represents such a case, where the flame height below the target element height is approximated by one cylinder, while the other cylinder is used to approximate the height of the flame for an elevated target. Depending upon the wind conditions, the two possible cases are shown the in Fig. 2 and 3.

In a no wind condition, the configuration/view factor may be obtained using the following mathematical relation [26]:

$$C_{f,1} = \frac{1}{\pi J}\tan^{-1}\left(\frac{k_1}{\sqrt{J^2-1}}\right) - \frac{h_1}{\pi J}\tan^{-1}\sqrt{\frac{(J-1)}{(J+1)}} + \frac{V_1 k_1}{\pi J\sqrt{V_1^2-1}}\tan^{-1}\sqrt{\frac{(V_1+1)(J-1)}{(V_1-1)(J+1)}} \tag{4}$$

$$C_{f,2} = \frac{1}{\pi J}\tan^{-1}\left(\frac{k_2}{\sqrt{J^2-1}}\right) - \frac{h_2}{\pi J}\tan^{-1}\sqrt{\frac{(J-1)}{(J+1)}} + \frac{V_2 k_2}{\pi J\sqrt{V_2^2-1}}\tan^{-1}\sqrt{\frac{(V_2+1)(J-1)}{(V_2-1)(J+1)}} \tag{5}$$

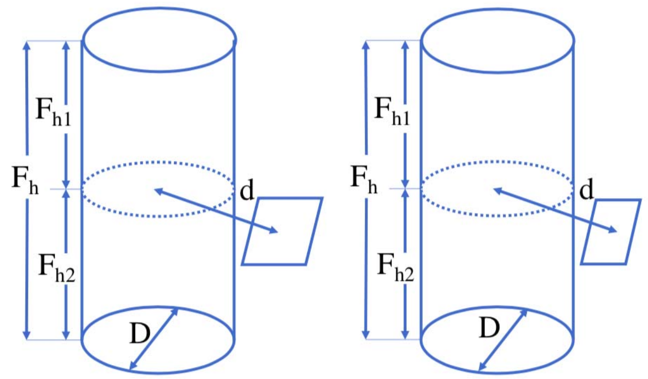


Fig. 1. View factor (Flame) for vertical and horizontal targets (wind absent and target at elevated level.

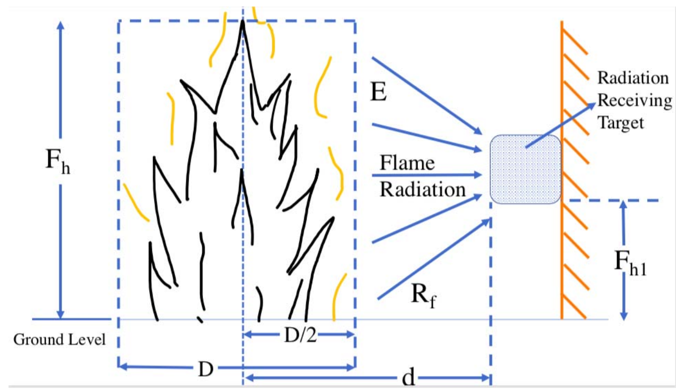


Fig. 2. Heat transmission model (wind free and target at elevated level).

where $J = \frac{2d}{D}$,$k_1 = \frac{2F_{h1}}{D}$, $V_1 = \frac{k_1^2+J^2+1}{2J}$, $k_2 = \frac{2F_{h2}}{D}$, $V_2 = \frac{k_2^2+J^2+1}{2J}$ and d represents the actual distance present between the flame's centre and the target (m), F_h represents the flame's (cylinder) height (m) and the corresponding diameter in (m) is given by D.

As such, for a given point, the view/configuration factor, can be obtained by calculating the vectorial summation of the two factors as given by:

$$C_{f,no-wind} = C_{f,1} + C_{f,2} \tag{6}$$

On the other hand, while considering significant wind in the environment, the fire flame is evidently curved and is considered to be tilted at an angle such that the deflection angle is mapped to the curved flame. As shown in the Fig. 3, the flame height, width and other configurations are depicted while considering a windy environment such that the wind velocity is given by (w_s) and the target is considered to be at an elevated level. In such conditions, in order to obtain the configuration/view factor (given by $C_{f,with-wind}$), the following mathematical expressions hold [26]:

$$C_{f_w,1} = \frac{g_1\cos\theta}{h - g_1\sin\theta} \times \frac{g_1^2 + (h+1)^2 - 2h(1+g_1\sin\theta)}{\sqrt{G_1 H_1}}$$

$$\times \tan^{-1}\sqrt{\frac{G_1}{H_1}}\sqrt{\frac{(h-1)}{(h+1)}} + \frac{\cos\theta}{\sqrt{N}} \times \left(\tan^{-1}\frac{g_1 h - (h^2-1)\sin\theta}{\sqrt{h^2-1}\sqrt{N}} + \tan^{-1}\frac{(h^2-1)\sin\theta}{\sqrt{h^2-1}\sqrt{N}}\right) - \frac{g_1\cos\theta}{(h-g_1\sin\theta)} \times \tan^{-1}\sqrt{\frac{(h-1)}{(h+1)}} \tag{7}$$

$$C_{f_w,2} = \frac{g_2\cos\theta}{h-g_2\sin\theta} \times \frac{g_2^2+(h+1)^2-2h(1+g_2\sin\theta)}{\sqrt{G_2H_2}} \times \tan^{-1}\sqrt{\frac{G_2}{H_2}}\sqrt{\frac{(h-1)}{(h+1)}} + \frac{\cos\theta}{\sqrt{N}} \times \left(\tan^{-1}\frac{g_2 h - (h^2-1)\sin\theta}{\sqrt{h^2-1}\sqrt{N}} + \tan^{-1}\frac{(h^2-1)\sin\theta}{\sqrt{h^2-1}\sqrt{N}}\right) - \frac{g_2\cos\theta}{(h-g_2\sin\theta)} \times \tan^{-1}\sqrt{\frac{(h-1)}{(h+1)}} \tag{8}$$

where

$$\begin{aligned}
g_1 &= \frac{2F_{h1}}{r},\\
g_2 &= \frac{2F_{h2}}{r} = \frac{2(F_h - F_{h1})}{r},\\
h &= \frac{d}{r}\\
G_1 &= g_1^2 + (h+1)^2 - 2\ g_1\ (h+1)\sin\theta\\
G_2 &= g_2^2 + (h+1)^2 - 2\ g_2\ (h+1)\sin\theta\\
H_1 &= g_1^2 + (h-1)^2 - 2\ g_1\ (h-1)\sin\theta\\
H_2 &= g_2^2 + (h-1)^2 - 2\ g_2\ (h-1)\sin\theta\\
N &= 1 + (h^2-1)\cos^2\theta
\end{aligned}$$

and F_{h1} = elevation level of target measured from the ground level (m), F_h = the length, in (m), of the fire flame (cylindrical flame). $r = \frac{D}{2}$ = the radius of the fire flame measured in (m), d = actual distance between the target and the fire pool (centre) measured in (m). θ = angle of deviation measured in $(radians)$.

The windy environment results in a change in the mathematical expression and may be given as follows [29]:

$$F_h = 55D\left(\frac{M_b}{\rho_a\sqrt{A_g D}}\right)^{0.67} W_v^{-0.21} \tag{9}$$

where: D = diameter or the total width of the fire pool measured in (m) M_b = fuel burning rate measured in $(kg/m^2/s)$, ρ_a = air density measured in (kg/m^3), A_g = acceleration due to gravity measured in (m/s^2), W_v = non-dimensional wind velocity which is given by the following:

$$W_v = \frac{w_s}{\left(\frac{A_g M_b D}{\rho_a}\right)^{1/3}} \tag{10}$$

where: w_s = speed of the wind measured in (m/s)

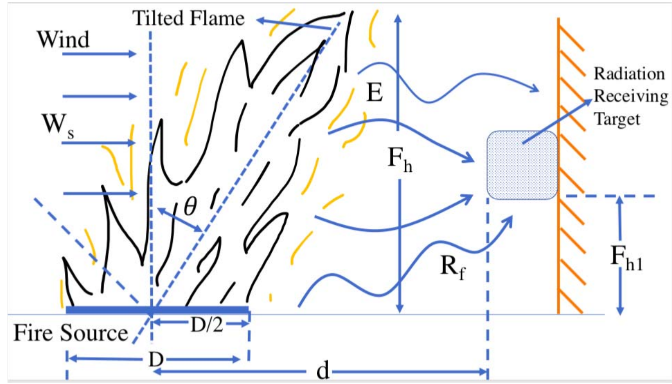


Fig. 3. Heat transmission model (wind present and target at elevated level).

The mathematical formulation to calculate the angle of deviation of the fire flame is given by (θ), and as per the American Gas Association (AGA) data, it is given by the following:

$$\cos\theta = \begin{cases} 1, & \text{for } W_v \le 1 \\ \frac{1}{\sqrt{W_v}}, & \text{for } W_v > 1 \end{cases} \tag{11}$$

As explained earlier, for a given point, the view/configuration factor, can be obtained by calculating the vectorial summation of the two factors as given by:

$$C_{f,with-wind} = C_{f_w,1} + C_{f_w,2} \tag{12}$$

Using (2) and (6) (if wind speed is not significant) or (12) (if wind speed is significant), the temperature of fire is calculated by:

$$T = \sqrt[4]{\frac{R_f}{\varepsilon \times \sigma \times C_f}} \tag{13}$$

2) Humidity: To calculate the humidity of the location, two parameters are required. These parameters are temperature (T) and dew point (D_p). The temperature of the location can be calculated using the equation (13). The dew point can be assessed using the nearest weather station website of the particular location. The relative humidity (Rh) is calculated using the following:

$$Rh = \frac{A_{vp}}{S_{vp}} \times 100 \tag{14}$$

where A_{vp} is the actual vapor pressure, and S_{vp} standard vapor pressure. The actual vapor pressure and standard vapor pressure are calculated as [30]:

$$A_{vp} = 6.11 \times 10 \times (\frac{7.5 \times D_p}{237.3 + D_p}) \tag{15}$$

$$S_{vp} = 6.11 \times 10 \times (\frac{7.5 \times T}{237.3 + T}) \tag{16}$$

B. Fuzzification

The process of fuzzy inference is best defined as the process of inferring knowledge by making use of the fuzzy rules and logic, defined on the basis of prevalent knowledge. The mapping, thus obtained, to match a given input of a model to the output generated by the model, is the building block of the fuzzy rules based on which, decisions are made. The proposed solution is based on the logic that human interpretation of data might result in inaccurate estimation. Hence, a fuzzy inference model is proposed to develop a fuzzy index for measuring the forest fire indexes and deals with the uncertainty present in the data. The initial steps involve, defining the parameters to be used for input and output. The input variables are defined through a membership function which is further used to generate the outputs of the model. The proposed model is based on four distinguished parameters, specifically the area temperature, the relative humidity, the measured wind speed and the measured smoke density in the area is considered while defining the rules. Depending upon the requirements of the model, i.e. to predict the possibility of future fire outbreak or to predict the existing fire outbreak, different combinations of the said rules are used for the inference process. The parameter and or rule selection is based on the correlation structure of the environmental behaviour. The observed values of the parameters are fuzzified into a membership function corresponding to the respective parameter. These membership functions define the meteorological variables under observation in the current study. Thus, for all the values of temperature, relative humidity, wind speed and smoke density, the proposed model delivers an observation that can be placed under 'low', 'medium', 'high', or 'extreme'. To have an accurate estimation of the parameters, the rule of thirty [27], which considers that a value of temperature and wind speed above the value of 30 $°C$ and 30 km/h, respectively, combined together with a value of relative humidity value below 30 % would result in a favourable environmental condition for a forest fire.

1) Input Fuzzification: The membership functions, thus obtained by fuzzifying the observed values of the respective parameters, have a membership value level equivalent to the i^{th} fuzzy set, such that the set is proposed for the variable V which has the values equal to "very low", "low", etc. Such values for all the measured parameters are summed to reach the final percentage of 100. The fuzzification involves the use of a trapezoidal function used as the membership function and is represented as follows:

$$\mu_A(x) = \begin{cases} 0, & \text{if } x < a \text{ or } x > r \\ \dfrac{x-a}{b-a}, & \text{if } a \leq x \leq b \\ 1, & \text{if } b \leq x \leq c \\ \dfrac{r-x}{r-c}, & \text{if } c \leq x \leq r \end{cases} \tag{17}$$

The lower limit of the parameters is given by a and that of the upper limit is given by r with the support limits for the two cases respectively given by b and c such that the following relation holds:

$$a < b < c < r \tag{18}$$

Considering the last measured value of each of the measured parameters for fuzzification, along with the last calculated risk value associated with every parameter, an average value is calculated and used to obtain the membership function for all the linguistic variables such that the average values may be expressed in the form of ranges for instance, 'low', 'medium', 'high' and 'extreme'. As explained above the membership value is obtained from the meteorological variables under consideration, and that the changes in the environmental conditions are random and frequent, the average value thus calculated might vary slightly.

2) Inference-Rule Evaluation: The proposed fuzzy model takes its inspiration from the model proposed in [31] and [32], popularly known as the TSK model. The set of fuzzy rules is given by $\{R\}$ such that $R_1, \ldots, R_{|R|} \in R$. The rules are driven by premise and consequences, such that the consequences may be obtained by obtaining a linear summation of the input variables, thereby representing a hyperplane that may be mapped in the input-output plane. The pre-condition/premise of the proposed fuzzy rule, given by R_r, $1 \leq r \leq |R|$ may be obtained by obtaining the conjunction of n_r fuzzy clauses such that the clauses are of the form u_{ijr} is F_{jr}. To put it in simple terms, the input variables, given by n_r, given in the index I_r, are considered. Considering the completeness of a fuzzy rule is mandatory, the use of the index set is quite justified since all the variables in u_j, $J = 1, \ldots, N$, need not be considered. The preconditions, as such, are responsible for defining a subspace of the given input space.

Thus, the fuzzy rule to start with i.e. R_1 is satisfied with $I_r \neq \phi$ if $u_{i_{1r}}$ is F_{1r} and ... and $u_{i_{nr}r}$ is $F_{n_r}r$ then $f_r = p_{0r} + p_{1r} \cdot u_1 + \cdots + p_{Nr} \cdot u_r$

with f_r representing the reverberation value of the rule. The reverberation or the consequence is given by its parameters $p_{0r}, \ldots, p_{Nr}, p_{jr} \in \mathbb{R}$.

The proposed approach uses a trapezoidal membership functions in order to represent the precondition's fuzzy sets F_{jr}, such that they may be defined for $r = 1, \ldots, R$ and $m = 1, \ldots, M$ and $\forall j \in I_r$; $u_{jm} \in \mathbb{R}$ as given in (17).

The rth rule's strength w_r for the input vector $\boldsymbol{u}_m$ with $m = 1, \ldots, M$; $\boldsymbol{u}_m \in U_1 \times \cdots \times U_N$; $U_l \subset \mathbb{R}$ is given by

$$w_r(\boldsymbol{u}_m) = \prod_{j \in I_r} F_{jr}(u_{jm}) \tag{19}$$

For $r = 1, \ldots, R; \forall \in U_1 \times \cdots \times U_N$ defines the strength (normalized) $v_r(\boldsymbol{u})$ as

$$v_r(\boldsymbol{u}) := \frac{w_r(\boldsymbol{u})}{\sum_{i=1}^{R} w_i(\boldsymbol{u})} \tag{20}$$

where $\sum_{k=1}^{r} v_k(\boldsymbol{u}) = 1$.

The proposed fuzzy model thus performs a mapping $\hat{y}$: $U_1 \times \cdots \times U_N \mapsto Y$ with $U_j \subset \mathbb{R}$ and $y \in \mathbb{R}$.

In order to calculate the crisp output of the model, the product inference may be used as the fuzzy inference along with the weighted average for obtaining the defuzzification value, and is given as:

$$\hat{y}(\boldsymbol{u}) = \frac{\sum_{i=1}^{R} w_r(\boldsymbol{u}) \cdot f_r(\boldsymbol{u})}{\sum_{i=1}^{R} w_r(\boldsymbol{u})} \tag{21}$$

3) Learning Model: Learning may also be understood as re-calibrating the parameters of a model with respect to a training dataset. In the proposed method, the entire set of parameters were optimized with respect to the premise and consequences of the rules. Thus, breaking the general problem into a set of two distinct problems, one being the premise parameter optimization problem and the other being consequence parameter optimization problem. The former being a nonlinear problem of optimization while the latter may be reduced to a linear problem of optimization [31], [33]. The task of parameter optimization is achieved by minimizing the global modelling error, such that

$$\|\boldsymbol{\epsilon}\|^2 = \left\| \boldsymbol{y} - \hat{\boldsymbol{y}} \right\|^2 \tag{22}$$

where $\hat{\boldsymbol{y}} := (\hat{y}_1, \ldots, \hat{y}_M)^T$ for $m = 1, \ldots, M$

In the proposed work, a well known and powerful technique of optimization, RPROP, is used for optimizing the premise parameters as the technique is relatively faster and easier than its challengers for instance simple gradient descent methods. As for the other half of the optimization, singular value decomposition (SVD) is used to generate stable solutions [34].

Let there be a matrix A of the order $M \times (R + 1) \cdot R$ and is defined as the collection of linear equations. With v_r as in (20) and the vector of the consequence parameter, given by, $\boldsymbol{p} := (p_{01} p_{11} \ldots p_{N1} \ldots p_{0R} p_{1R} \ldots p_{NR})$, the model output $\hat{\boldsymbol{y}}$, may be given as:

$$\hat{\boldsymbol{y}} = A \cdot \boldsymbol{p} \tag{23}$$

The minimal error, is dependent upon the parameters p_k, and is given by:

$$\frac{\partial \|\boldsymbol{\epsilon}\|^2}{\partial p_k} = 0 \tag{24}$$

such that the error is represented by $\|\boldsymbol{\epsilon}\|^2$.

Considering the Euclidean norm L_2 for $\|\cdot\|$ for $k = 1, \ldots, (N + 1) \cdot R$:

$$\frac{\partial \|\boldsymbol{\epsilon}\|^2}{\partial p_k} = \sum_{m=1}^{M} 2\left(y_q - \sum_{j=1}^{(N+1)\cdot r} a_{mj} p_j \right)(-a_{mk}) = 0 \tag{25}$$

Using (23) and (25) we obtained

$$\boldsymbol{p} = ((A^T A)^{-1} A^T)\boldsymbol{y} \tag{26}$$

The SVD is thus used for the regression equations (linear), as above, to calculate U, D and V such that $A = UDV^T$, where $U^T U = E, D$ is diagonal, and V is orthogonal. Consequently,

$$\boldsymbol{p} = V D^{-1} U^T \boldsymbol{y} \tag{27}$$

The use of SVD is limited to initial linear fuzzy models only and RPROP is used for iteratively adopting all the other parameters in a simultaneous fashion.

V. Metrics for Evaluation

Fire index is considered as the measure of *probability of fire* in the forest region. Four meteorological variables namely *Temperature, Humidity, Wind Speed* and *Smoke*, are considered as the factors affecting the occurrence and accurate detection of fire in the forest. For all the four meteorological variables, the degree of membership is considered in four categories which are *Low, Medium, High* and *Extreme*. A total of 256 fuzzy rules were generated to obtain the effect of {Temperature, Humidity}, {Temperature, Wind Speed}, {Temperature, Smoke}, {Humidity, Smoke}, {Humidity, Wind Speed}, {Smoke, Wind Speed} on fire index.

The effect of event classification and intensity discrimination on the accuracy of event detection and inference is measured by a comparative analysis made on a set of 20,000 events.

Algorithm 1 EIDAER

1: *Initialization:* Sensor nodes gather environmental parameters {t-temperature, h-humidity, w-wind speed, s-smoke}.
2: **procedure** INTENSITY–DISCRIMINATION
3: Compute view factor (C_f) using 6 (very low wind) or 12 (with wind)
4: Compute temperature $T = \sqrt[4]{\frac{R_f}{\varepsilon \times \sigma \times C_f}}$
5: Compute relative humidity $Rh = \frac{A_{vp}}{S_{vp}} \times 100$
6: **end procedure**
7: **procedure** FUZZIFICATION
8: Fuzzify environmental parameters using (17)
9: Compute crisp values using $\mu_A(x)$ and $\hat{y}(\boldsymbol{u}) = \frac{\sum_{i=1}^{R} w_r(\boldsymbol{u}) \cdot f_r(\boldsymbol{u})}{\sum_{i=1}^{R} w_r(\boldsymbol{u})}$
10: **end procedure**
11: **procedure** LEARNING MODEL
12: $\hat{\boldsymbol{y}} = A \cdot \boldsymbol{p}$
13: $\boldsymbol{p} = ((A^T A)^{-1} A^T)\boldsymbol{y}$
14: Compute learning parameters $\boldsymbol{p} = V D^{-1} U^T \boldsymbol{y}$
15: **end procedure**
16: Fire Probability Output:={low, medium, high, extreme}

VI. Results and Discussion

A. Experimental Setup

An accidental fire site was used for the experimental setup shown in Fig. 4 which is a partial view of the experimental testbed. Scientech 6205L IoT builder module, Scientech 6205N Sensor node, Digital temperature and humidity sensor, multichannel gas sensor and Scientech 6205G gateway module for connectivity were used for gathering the experimental data. The Scientech 6205L is an IoT builder that can be programmed in C and python [35]. It supports real-time program writing, high-performance switching power supply with three low power sleep modes, peer-to-peer networking, automatically arbitrating wireless contention, flash memory for data and indoor vs. outdoor antenna options. The R_C, R_S and other parameters of the nodes were considered as per the hardware specification sheet. The readings were taken from a safe distance and the actual recorded temperature was $48°C$ with a humidity value of 30%. The values were recorded for about 20 minutes with 10 samples per second. Owing to the special case of forest fires, a significantly harsh terrain with factors such as limited sensing range, frequent node and link loss, limited line of sight, noise due to animal presence etc. is also considered for the experimental data gathering.

(a)

(b)

Fig. 4. Experimental setup.

TABLE I
SIMULATION PARAMETERS

PARAMETER	VALUE
Area	$300m \times 300m$
Number of nodes (n)	500
Communication Range (R_C)	$50m$
Sensing Range (R_S)	$25m$

B. Simulation Setup

A randomly deployed network of five hundred sensor nodes was simulated to replicate a forest environment. The nodes were deployed to report four different but simultaneously occurring meteorological variables in an area of $300m \times 300m$. The reported meteorological variables were based on the recorded observations and analysis of four variables, namely *Temperature, Humidity, Wind Speed* and *Smoke*. With a total of 1024 sampling points, the events were stored in a column vector with an appropriate class label for training and testing. Each sampling signal was subjected to 10 different kinds of white Gaussian noise resulting in 20, 000 fragments. The remaining parameters for the simulation study are given in Table I.

C. Results

1) Membership Functions of Meteorological Variables: The proposed fuzzy system is driven by four meteorological variables, namely *Temperature, Humidity, Wind Speed* and *Smoke*, which are considered to be the prime factors and/or indicators of the forest fire. The values of these four meteorological variables, as sensed and reported by the deployed network, are fed to the proposed fuzzy model as the input. The fuzzified values of the variables are obtained by a membership function, proposed for every meteorological variable (shown in the Fig. 5), such that the degree of membership for each of the observed input fed to the system with the four fuzzy sets (Set_{Tp}, Set_{Hd}, Set_{Wd} and Set_{Sk}), is given on the 'Y' axis. Correspondingly, the domain of the meteorological variables is represented on the 'X' axis. The proposed fuzzy system is aimed at obtaining 'low', 'medium', 'high', or 'extreme' for every fuzzified value.

TABLE II
NOTATION DESCRIPTION

Notation	Description
z	Variable
ζ_z	Discreet Value of z
D_z	Domain of z
S_{z_i}	Fuzzy set i of z
$\xi_{S_{z_i}}\zeta_z$	Degree of Membership $zeta_z$ for corresponding S_{z_i}

TABLE III
FUZZY SET AND DOMAIN FOR VARIABLES

Variable Name	Set	Domain
Temperature (T)	Set_T = {low, medium, high, extreme}	$\{0, 100\}$ *°C*
Humidity (*Rh*)	Set_{Rh} = {low, medium, high, extreme}	$\{0-100\}$ *%*
Wind (*Wd*)	Set_{Wd}= {low, medium, high, extreme}	$\{0-240\}$ *km/h*
Smoke (*Sk*)	Set_{Sk} = {low, medium, high, extreme}	$\{0-100\}$ *ppm*

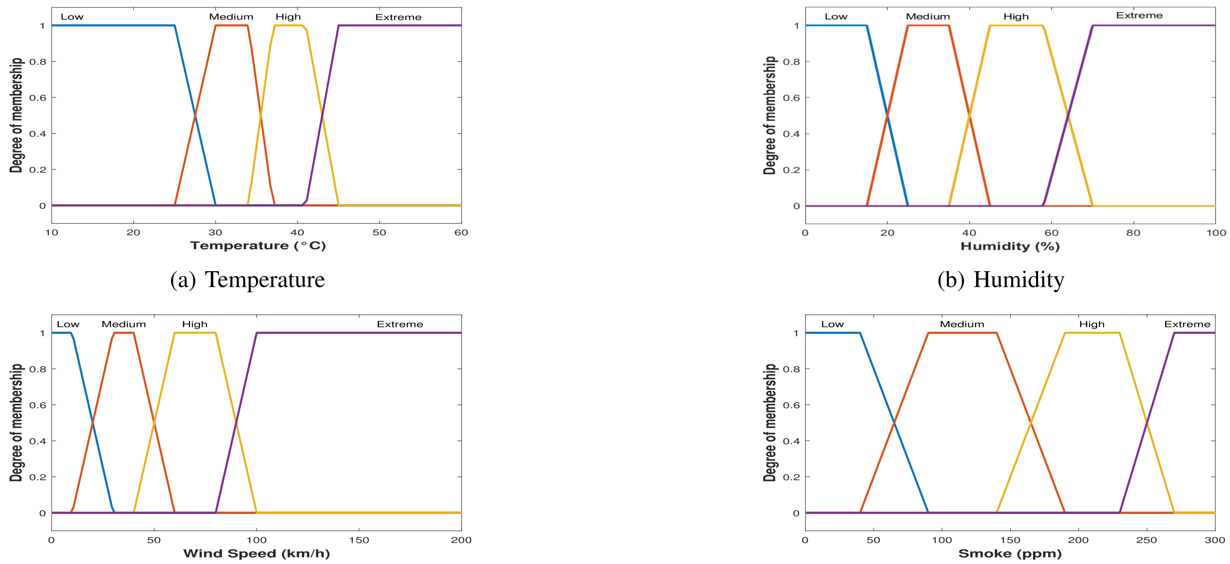
The fuzzy sets, as described above, are defined by the rule of thirty [27]. The proposed fuzzy rules also consider the significance of *smoke* as a prime indicator for forest fire detection. The sets thus obtained, represents the reporting of significant and/or unusual change in the natural habitat. The rule is significant in highlighting the fact that an unusual activity, if and when detected, represents a high probability of forest fire in the region.

Therefore, for a given z, the value of ζ_z ranges between the defined domain limits {x,y} of D_z. The respective membership functions are responsible for fuzzifying this value to calculate the $\xi_{S_{z_i}}\zeta_z$ (refer Table II). To obtain the final value, the degree of membership for all the sets is summed i.e.

$$\forall z \in (T, Rh, Wd, Sk)\exists\zeta_z \in [x, y]| \sum_{i=4}^{4} \xi_{S_{z_i}}\zeta_z \quad (28)$$

2) Rules: The If-Then rules, for the proposed fuzzy logic method, are defined on various permutations of the proposed membership functions. It is observed that there is an exponential growth in the rule base as the dimension and complexity of a system increases. A total of 256 fuzzy rules (as shown in Fig. 6 were generated to obtain the effect of {Temperature, Humidity}, {Temperature, Wind Speed}, {Temperature, Smoke}, {Humidity, Smoke}, {Humidity, Wind Speed}, {Smoke, Wind Speed} on fire index.

3) Temperature: Fig. 7a shows a three dimensional (3D) view of the *Fire-index* with respect to *Humidity* and *Temperature*. On the other hand, Fig. 7b and Fig. 7c, reflect the *Fire-index* with respect to *Wind Speed* and *Temperature* and *Fire-index* with respect to *Smoke* and *Temperature*. The



(a) Temperature (b) Humidity

(c) Wind (d) Smoke

Fig. 5. Membership functions of meteorological variables.

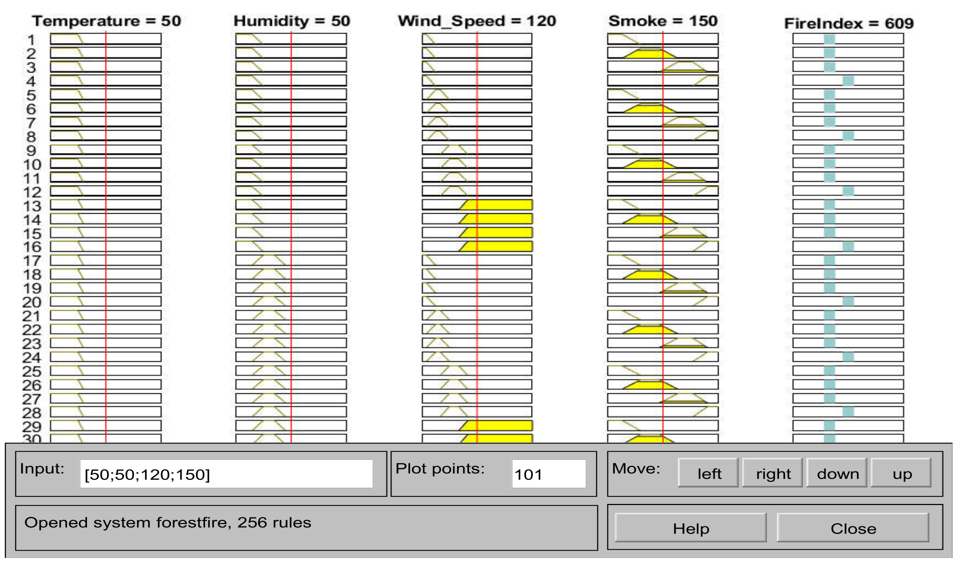
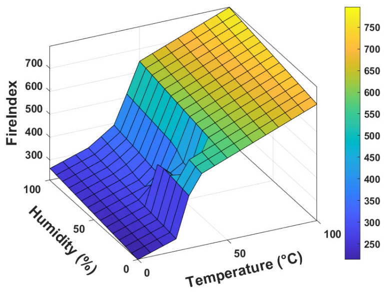
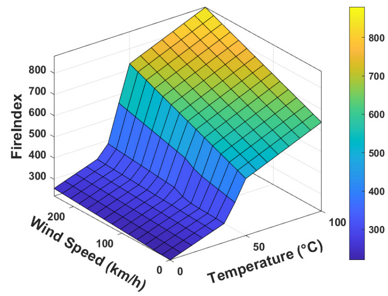


Fig. 6. An instance of fuzzy rules generator (temperature in $^\circ C$, humidity in $\%$, wind speed in km/h and smoke in ppm).

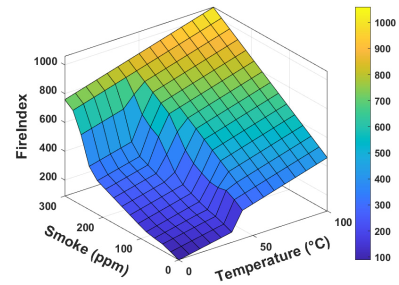
recorded observations, as reflected in the 3D view, shows that at higher temperature values, the value of the fire index tends to reach higher. The high value of the fire index is further fuelled to reach the extreme values when the humidity value is low and the wind speed is high. The temperature plays a more direct role in the forest fire as the generated heat fulfils the ignition requirement and propels the combustion and its continuation. The earth's surface is heated by the sun's heat (radiation), and this in turn increases the temperature of the region close to the surface. The radiation, reflected from the earth's surface, is absorbed by water molecules present in the air thereby increasing the air temperature. One of the other factor which propels the rate of fire combustion and propagation is the forest fuel temperature. Although the loss in temperature follows the standard adiabatic lapse rate, the sun's radiation affects the forest fuels directly, and thus the amount of heat required for ignition, in such a scenario, is significantly reduced. A warmer and drier forest fuel requires significantly less energy to reach the ignition threshold. As a result, forest fires are often ignited and propelled in the afternoon, when the sun is at its peak, forest fuels are warmer and relative humidity is low. The effect is clearly seen in Fig. 7a where the effect of high temperature and low humidity is reflected in terms of high fire index. A silent reason, apart from temperature, is the surface. In a forest region, the trees absorb most of the heat reflected from the surface and directly from the sun as well. However, the combined effect of temperature, friction, humidity and wind, ignites the fire in the drier parts of the



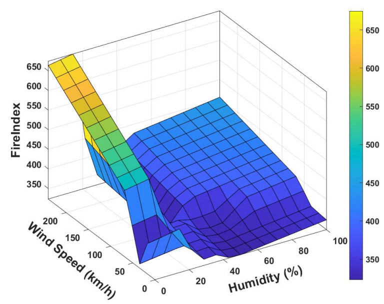
(a) Temperature and Humidity



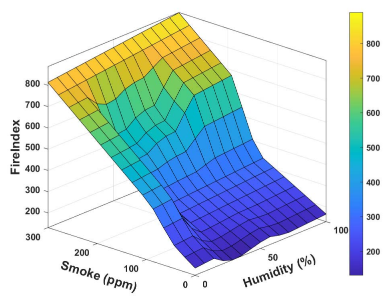
(b) Temperature and Wind Speed



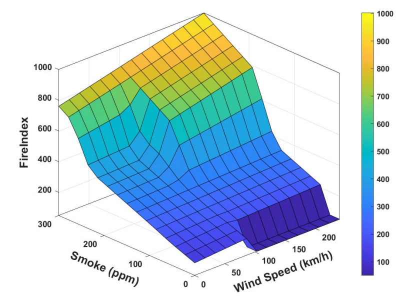
(c) Temperature and Smoke



(d) Humidity and Wind Speed



(e) Humidity and Smoke



(f) Smoke and Wind Speed

Fig. 7. Fire index w.r.t four meteorological variables (i.e. Temperature, Humidity, Wind Speed, and Smoke.

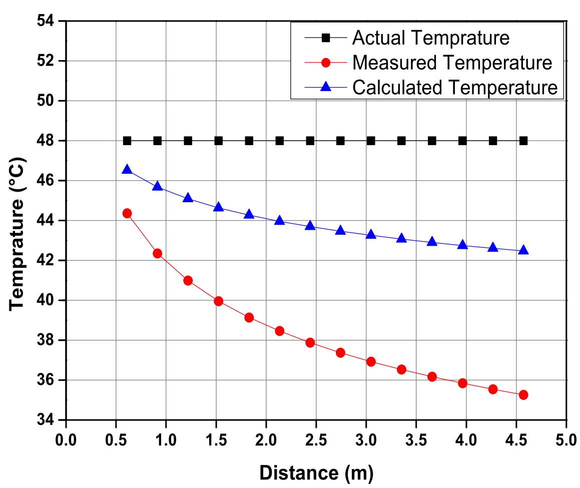


Fig. 8. Temperature.

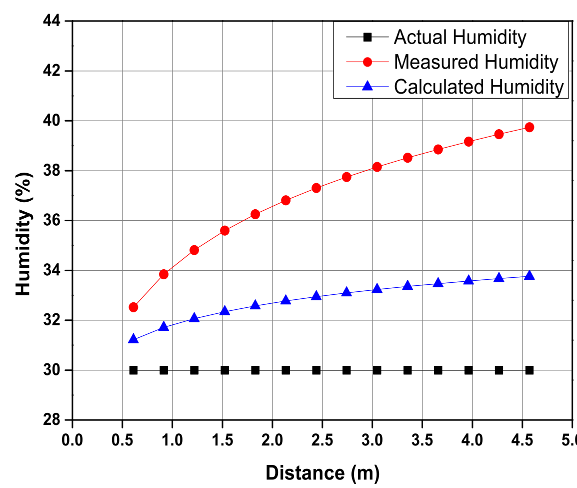


Fig. 9. Humidity.

vegetation. A clear indicator and probably the most accurate inference provider of high fire index is the smoke intensity in the region (Fig. 7c). A high temperature, combined with a high smoke density, is bound to have a high fire index and the same may be observed from the high peaks as reflected in Fig. 7c.

4) Humidity: The relative humidity is defined as the ratio of "actual water vapour in the atmosphere compared to the amount of water vapour that would saturate the atmosphere at that temperature". This in turn reflects the impact the water vapour in the atmosphere can have on the ignition, combustion, intensity and propagation of forest fire. To put in simple terms, and as clearly shown in Fig. 7a, 7d, and 7e, the low humidity can make the forest fire uncontrollable when combined with high temperature, wind and smoke. A low humidity value with low wind speed and a low temperature has a low impact on the fire index (Fig. 7d and 7a). However, even if the humidity is low but a high smoke density is a clear indicator of forest fire and has a high fire index value (Fig. 7e). It is evident from the mentioned 3D plots, that a lower humidity value propels the ignition of fire at a significantly higher rate and also propagates at a much higher rate. It is also to be noted that the relative humidity present in the air has a direct effect on the moisture content in the forest fuels. The direct reason for this being that the heat in the fuel is absorbed by the moisture and prevents the intensity of the fire to grow uncontrollably. The fuel's moisture is evaporated quickly in case of low humidity, however, a highly humid environment prevents quick evaporation of fuel's moisture, thereby preventing high intensity and rapid spread of fire. A close analysis of the diurnal cycle proves that the fluctuation in relative humidity is significant. The duration in the early morning witnesses a highly humid atmosphere whereas degrades as the day progresses until it is at its peak in the noon reflecting that as the temperature increases, relative humidity is inversely affected and goes down.

An important aspect of relative humidity is rainfall, which affects the content of the moisture in the air and in forest fuels, immediately. A direct effect of rainfall and/or snowfall results in a reduction in temperature along with dampened ground, dampened forest fuels calmer wind, increased moisture level in the atmosphere and reduced fire index value. Therefore, for a fair analysis of the fire index value, it is important that the pattern of rainfall in the region must be considered. A general pattern highlights the duration between February and April as the peak season for forest fires as there is little or no rainfall. The dry leaves after the spring season act as a quick propagator and the dry air, high temperature and natural friction are powerful catalysts for a wildfire to start. In most of the cases, such a fire becomes uncontrollable and the same may be seen in the 3D plots (Fig. 7b and 7d where high fire index is reported for high temperature and wind speed is given that the humidity is low.

5) Wind Speed: Dry weather, coupled with high temperature with powerful wind conditions, is the perfect environment for an uncontrollable forest fire. The 3D plot shown in the Fig. 7b, 7d and 7f. As evident from the 3D plots, wind plays a vital role in determining the fire index value. Not only the direction of the wind dictates the propagation path of the fire, but it also drives the intensity of the fire as well. The unpredictability in the wind direction and speed makes it one of the most significant factors while monitoring and controlling forest fire. Not only an increased oxygen supply is facilitated by the wind, but it is also responsible for the drying of the fuel moisture thereby intensifying the growth of the fire. High-intensity wind, in dry weather (Fig. 7d), may cause the forest fuel to heat rather quickly, by pushing the flame towards the fuel. This may in turn cause the head of the fire to propagate rapidly and wildly. In windy weather, the fire sparks are propagated rapidly in every direction disabling the preventive measures to be undertaken. As evident from Fig. 7f, high-density smoke, propagated by high-speed wind results in a high fire index value, on the other hand, low wind speed integrated with high humidity and low temperature, is hardly a fire indicator (Fig. 7b and 7d).

6) Event Intensity Analysis: The results shown in Fig. 8 and Fig. 9 represent variation of *temperature* and *humidity*, respectively, for an average of twenty thousand reported observations. Both the figures have three distinct readings which are the *Actual Value*, *Measured Value* and the *Calculated Value*. As seen in Fig. 8 and Fig. 9, the actual temperature and humidity respectively, at the source, remains constant for a set of observations. However, the measured values and the calculated values vary as the distance is increased, which is quite understandable, considering the increased distance from the source. It must be noted that the variation in calculated values and the measured value in comparison to the actual temperature value is significant. Thus, to clarify and prove the efficacy of the proposed intensity inference, in case of an event, the measured temperature value at any node is represented by the *measured value* and is the only value available at the node. A mathematical formulation, as proposed, was designed to infer, the *actual temperature* or an approximate measure of the actual value, in order to reduce the error rate and improve the detection and discrimination intensity. The *calculated temperature*, represents the value reported by every node observing the event (as obtained in the proposed method) which shows a clear decrease in the error rate which can be clearly seen as 1.94% in the worst case. A similar observation of Fig. 9, shows the error rate to be of a nominal value of 2.01% proving the efficiency of the proposed approach in the terms of intensity discrimination and event inference.

VII. Conclusion

This paper presents an effective fuzzy rule-based accurate event detection mechanism for preventing forest fires. The proposed scheme was tested to determine the classification and intensity discrimination for accurate inference of forest fire in terms of fire index. A comprehensive analysis on four variables, namely *Temperature, Humidity, Wind Speed* and *Smoke*, and comparative analysis of the inference accuracy proves that the proposed fuzzy logic-based method classifier can infer the forest fire with about 98.7% accuracy. The analysis and results confirm that different permutations of *Temperature, Humidity, Wind Speed* and *Smoke* can be accurately used to infer and prevent forest fires. However, it must also be noted that the factors such as atmospheric stability, cloud development and surface are some of the many factors that may be considered in future in addition to the variables used in this study.

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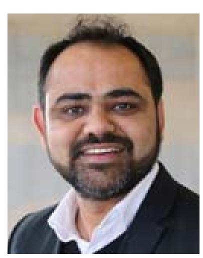

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