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A fuzzy inference and big data analysis algorithm for the prediction of forest fire based on rechargeable wireless sensor networks

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ABSTRACT

High incidence and destructiveness of forest fire determine the importance of forest fire prediction or early detection. we find that the observation of local weather and human behaviors are the most correlated to forest fire important factors. In this paper, a fuzzy inference and big data analysis algorithm is proposed to assess fire risk and calculated the quantitative potential fire risk. These factors converted to triangular fuzzy numbers are calculated by fuzzification and output fire rating level. The continuous 24-hour weather information, which can reflect the high accurate status of forest environment, is collected by the rechargeable wireless sensor network. The fuzzy reasoning system was evaluated for Nanjing City region, the capital of Jiangsu Province, China. The high possibility of potential forest fires risk can be measured by this algorithm, therefore we need to pay more attention to prevent forest fire condition.

1. Introduction

In general, the forest area or wildland has the high possibility to have forest fires and have a significant damage to the environment [1]. Forest, animal habitat and human death can be burned by forest fire [2,3]. Lighting [4], heat and aridity of unusual weather condition [5], and human activities [6] are the common reasons for forest fires. From 1952 to 2012, there are 798,500 forest fires due to the statistics in China and 38,060, 000 hectares of forest are destroyed which caused about $22 million an year and 13, 000 forest fires each year [7], as shown in Figs. 1 and 2. Particularly, the Daxing'anling forest fires shocked the whole country and the world in May 6, 1987, the official reports estimate the area as 1.14 million hm2 were burned, two cities and nine Forestry Center were eradicated. About 211 residents lost their lives, and 50, 000 residents were homeless. These astonishing statistical figures indicate that forest fires fatal threats to the world economy, and they can cause significant damage and destruction. These astonishing statistical figures indicate that forest fires fatal threats to the world economy, and they can cause significant damage and destruction.

There are numerous factors which can affect forest fire occurrence possibility. So it is important to develop an algorithm to prevent or predict the forest fire. The forest fire can be possible to be predicted to avoid the forest destroys. The number of forest fires never decline but still rise in hundreds of years to purse the principle of the origination of forest fire.

With the development of rechargeable wireless sensor networks [8], RWSNs has become a topic of much interest to researchers due to their wide-ranging applications. For example, they have been used in military applications, environmental applications, health applications and home applications [9], to name a few. Forest fire prediction can be implemented by the rechargeable wireless sensor networks based on the monitored factors which can be used to calculated the fores fire risk [10]. Human have the ability to obtain the information of forest environment using WSNs and analysis the relationship between the forest fire and these information [11].

The possibility or risk of forest fire is improved if one or more values of meteorological parameters reach the threshold, which is calculated by forest fire model or historical forest fire statistics. In this paper, we use fuzzy reasoning system to calculate the forest fire risk which is the prediction algorithm implemented by rechargeable wireless sensor networks. The fuzzy theory is utilized to analyze the causation from uncertain factors, which is according to the principle for analyzing the causes of forest fires. Our paper

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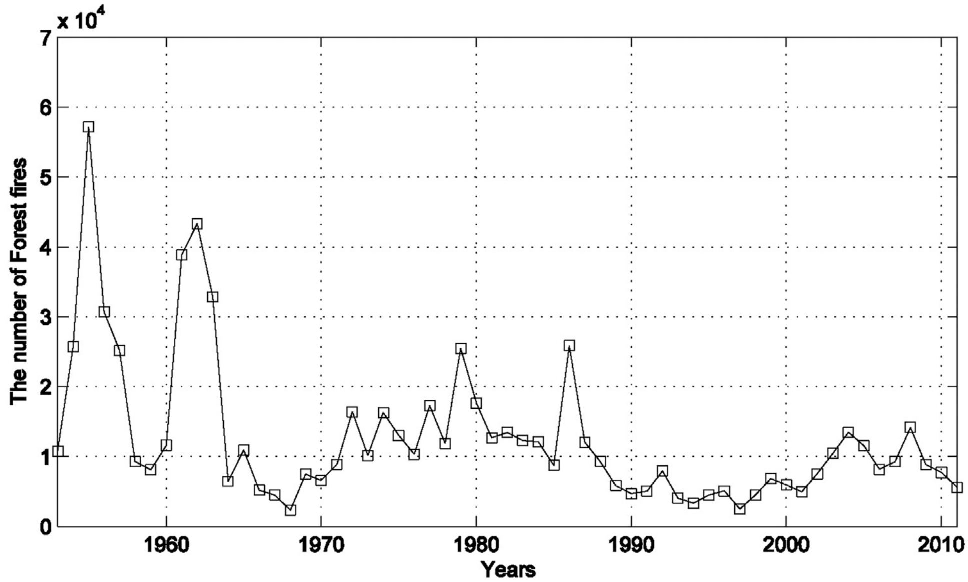


Fig. 1. The number of forest fire from 1953 to 2012 in China.

is organized as follows. In section II, we do some literature review of forest fire prediction and fuzzy reasoning. In section III, our forest fire prediction algorithm is proposed. Section IV established the experimental results and conclusions are given in section V.

2. Related Works

Several strategies were provided for forest fire prediction and detection using WSNs; e.g., [7,12,13]. A wildfire prevention system based on a time-driven wireless sensor was introduced in [14]. Sabit et al. built a TrueTime model of WSN architecture for wildfire prediction and analyze the network latency, energy consumption, and scalability [15]. Considering the forestry area usually is far away the infrastructure and it's impossible to replace the battery of sensors, a rechargeable WSNs system for forest monitoring is proposed [16,17]. In these works, the WSNs technologies are utilized for real-time collecting information generated by rechargeable sensors about the forest area, such as, temperature, relative humidity, wind speed and rainfall [10]. In order to analyze the relationship between the forest fire and these weather parameters, intelligent technology is paid more attention.

Intelligent system such as data mining technique is used to predict forest fire [11,14]. Make decision system [18] can be implemented by fuzzy reasoning scheme and fuzzy triangular number which can show fuzzy logic better than others, which have a number of application fields such as evaluation of risk and evaluation performance. Forest fire prediction [19] can be calculated by a fuzzy algorithm using five factors such as temperature, smoke, light, humidity and distance. A real time fire prediction algorithm [20] is developed by surface fore spread scheme using fuzzy linguistic and decision making model. Analytical Hierarchy Process with fuzzy logic [21] is also develop to predicate fores fire level risk by ranking the causative factors.

Although forest fire prediction can be implemented by fuzzy reasoning scheme, weighted fuzzy reasoning scheme still can not be utilized in forest fire prediction directly. In this paper, we use fuzzification of inputs data with weighted fuzzy reasoning algorithm based on rechargeable wireless sensor networks automatically and

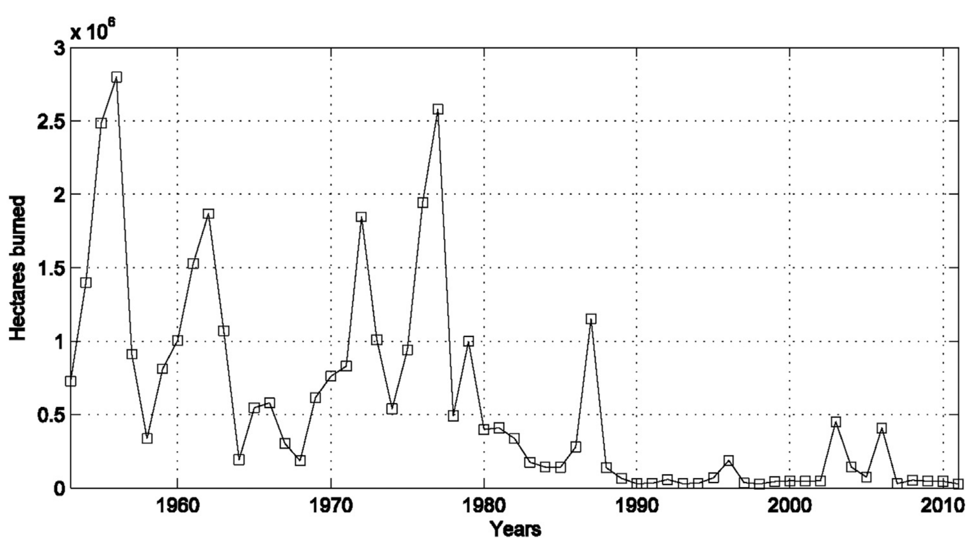


Fig. 2. The hectares burned from 1953 to 2012 in China.

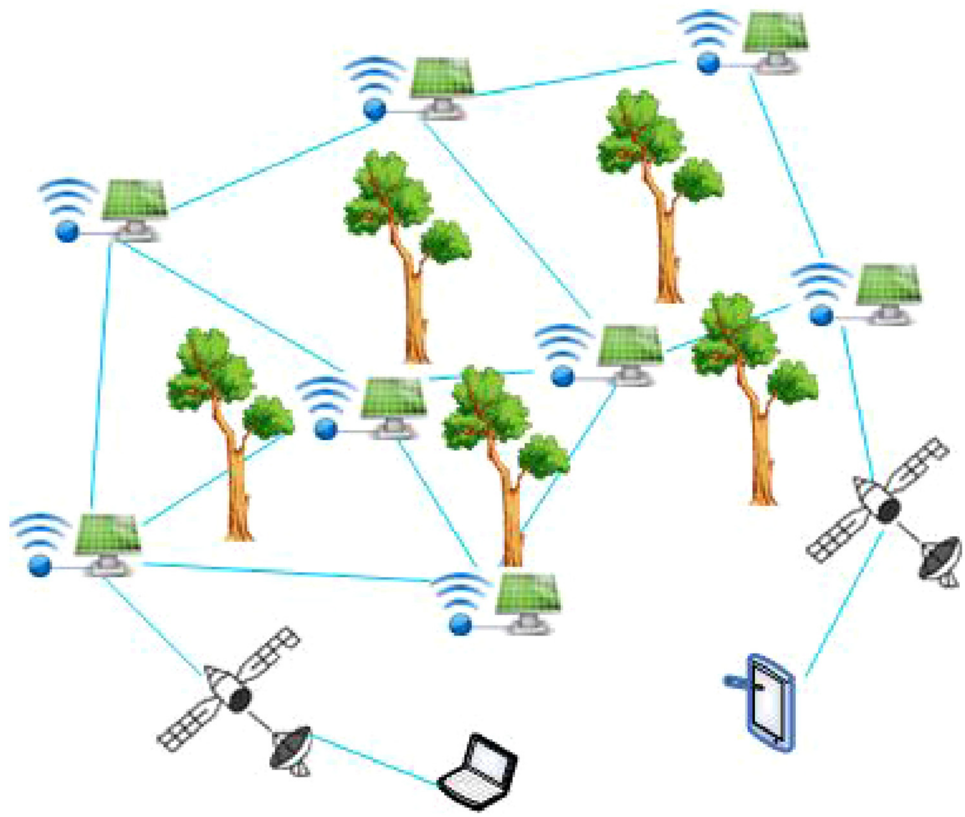


Fig. 3. Wireless sensors are deployed in forest area.

flexibility. Certainty factors of the real values are converted to fuzzy numbers by our weighted fuzzy scheme.

3. Proposed Algorithm

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation as well as the experimental conclusions that can be drawn.

3.1. Forest monitoring using wireless sensor networks

We can summarize the advantages of the fuzzy inference system which is implemented by rechargeable wireless sensor network as follows: first, due to the use of low-cost sensors, a certain number of wireless sensors can be deployed in remote forest areas. Therefore, compared with the traditional finite weather stations, we can now collect more weather parameter data, and can calculate more accurate results.Second, sensors convert energy from the natural environment, such as solar and wind energy. Therefore, the rechargeable sensors can be deployed anywhere to monitor the forest. The wild forest is usually few people tread area, stay away from the infrastructure. Therefore, it is unrealistic to establish a perfect weather station in this field. Now, it is a trend that the rechargeable wireless sensor will be widely used in the prevention and control of wildfire as is shown in Fig. 3.

There are many factors for forest fires. Temperature, relative humidity, precipitation, wind speed, season, date, time, historical fire data, population density, fuel type and the density of the bridge are the main factors of forest fires. For example, because more human activities result in holidays and during the day, the potential for forest fires is much greater than working hours and nights. In this paper, we divide these factors into three categories: weather factors, human behavioral factors and environmental factors, as the original input data. The probability of forest fire will be normalized after the fall in the range [0,1], as shown in Fig. 4.

Table 1
Fire fuzzy rules for fire prediction problem.

Temp					
Hum	Low	Moderate	High	Very High	Extreme
Extreme	Low	low	Low	Moderate	Moderate
Very High	Low	Low	Moderate	Moderate	High
High	Low	Moderate	Moderate	High	High
Moderate	Moderate	Moderate	High	High	Very High
Low	Moderate	High	High	Very High	Extreme

3.2. The relevant parameter specification

The number of input variables of our system is specified for each membership function.According to the weather characteristics of the monitoring area, the temperature range of −10 °C to 40 °C, humidity of 0–100%, respectively, defined as low, medium, high, very high, very high in the range of five, as shown in Fig. 3. In this paper, we transform the concept of linguistic variables from one process to the other. The selected input parameters will determine the extent of the variable depending on which level will be drawn to the upper horizontal axis and perpendicular to the true upper boundary. Probability of forest fire changing with temperature is shown in Fig. 5 (a). The horizontal axis represents the input temperature range from −10C to 40 degrees, and the vertical axis is the standard value of the forest fire potential. The probability of forest fire risk of changing with humidity is shown in Fig. 5(b).

High temperature and low humidity indicate more potential of fire occurrence, and vice versa. With the same assumptions, new rules can be produced if desired, as is illustrated in Table. 1. From the Table.1, we can observe five levels of temperature and humidity

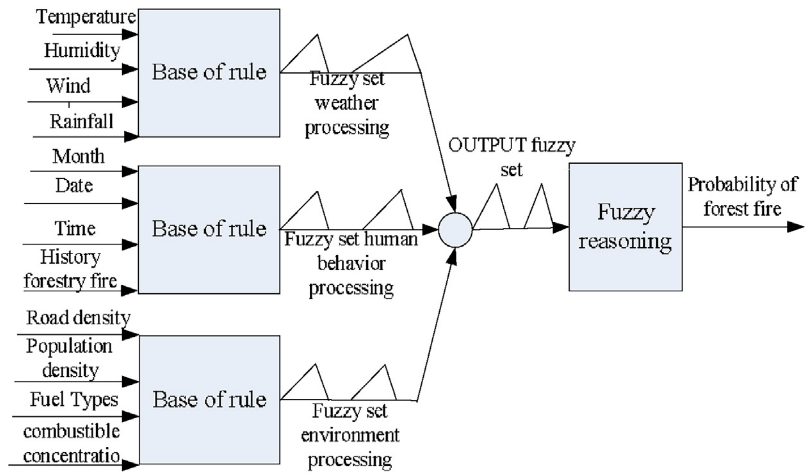
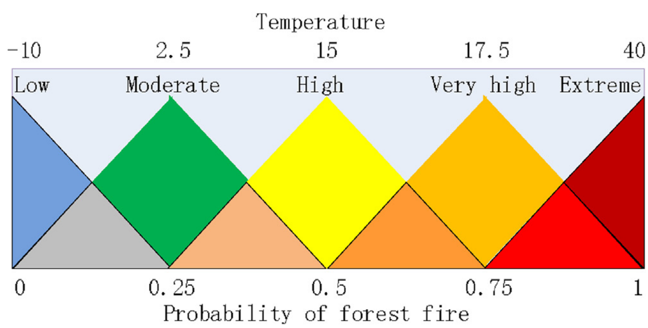
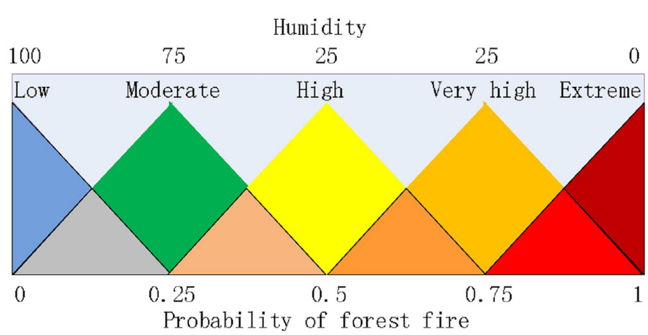


Fig. 4. Forest fire prediction based on fuzzy reasoning system.



(a)The probability of forest fire with temperature



(b) The probability of forest fire with humidity

Fig. 5. Probability of forest fire in according with the different levels of temperature and humidity.

are inputted, and twenty five results are outputted, which shows an alternative way to demonstrate fuzzy rules for forest fire prediction. Even though this rule is easy to be understood and implemented simply, when there are twelve variables as input data, the output data will be more than 200 million. It is almost impossible that convert these outputs to five forest fire risk levels. Therefore, we should improve the fuzzificaiton efficiently and a new fuzzy triangular number algorithm is proposed for predicting forest fire.

3.3. *Triangular number fuzzification scheme*

There is a continuous value between 0 to 1 of our fuzzy scheme, which is an approximate number. Triangular is the mostly used shapes for fuzzy scheme. In this paper, we choose triangular number as the fuzzy decision system. We have temperature, humidity, wind speed and rainfall as the input of fire prediction scheme. The probability of fire output, there are five variables are as follows: Low, moderate, high, very high, extreme.Analyzed by the similarity of users, the results show that the triangular fuzzy comprehensive evaluation on the expression of the number of users can be items; triangular fuzzy number judgment can be better. We assume, $a < b < c$, $\mu = (a, b, c)$ is called a fuzzy triangular number and its membership function can be expressed as follows:

$$\mu(x) = \begin{cases} \dfrac{x-a}{b-a}, x \in [a, b] \\ \dfrac{c-x}{c-b}, x \in [b, c] \\ 0, x \notin [a, c] \end{cases} \tag{1}$$

Where, $L(x) = \frac{x-a}{b-a}$, $x \in [a, b]$ is a increasing function and continuous on the right, and $R(x) = \frac{c-x}{c-b}$, $x \in [b, c]$ is a decreasing function and continuous on the left, and $0 \le L(x), R(x) \le 1$.

Let $A_1 = (a_1, b_1, c_1)$ and $A_2 = (a_2, b_2, c_2)$ are two fuzzy triangular numbers, their calculation rules are as follows:

1 Triangular fuzzy numbers addition

$$A_1 \oplus A_2 = (a_1, b_1, c_1) \oplus (a_2, b_2, c_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{2}$$

2 Triangular fuzzy numbers multiplication $\otimes$

$$A_1 \otimes A = (a_1, b_1, c_1) \otimes (a_2, b_2, c_2) = (a_1 * a_2, b_1 * b_2, c_1 * c_2) \tag{3}$$

3 Triangular fuzzy numbers division based on method 1 $\odot$

$$A_1 \odot A = (a_1, b_1, c_1) \odot (a_2, b_2, c_2) = \left(a_1/a_2, b_1/b_2, c_1/c_2\right) \tag{4}$$

4 Triangular fuzzy numbers division based on method 2 $\oslash$

$$A_1 \oslash A = (a_1, b_1, c_1) \oslash (a_2, b_2, c_2) = \left(a_1/c_2, b_1/b_2, c_1/a_2\right) \tag{5}$$

Where, $0 < a < b < c$, for Eqs. (3), (4) and (5). In our work, all fuzzy triangular numbers are positive and their range are [0,1].

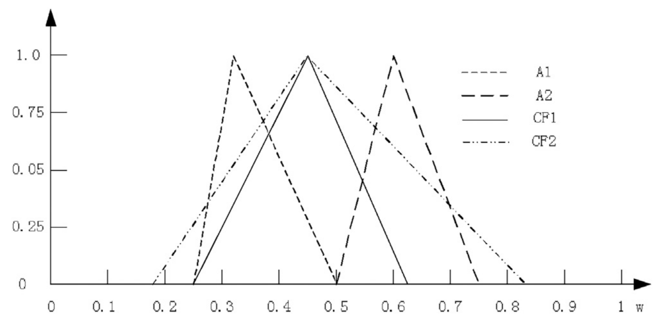


Fig. 6. Probability of forest fire over fuzzy triangular numbers.

3.4. Weighted Fuzzy Reasoning Algorithm

In this paper, we use a weighted fuzzy algorithm as the fire prediction scheme which is shown as follows.

Case 1. It is assumed that there is a fuzzy production rule in the knowledge base of rule base R:

$$R : \text{if} A_1 (w_1) \text{and} A_2 (w_2) \text{and} \cdots A_n (w_n)$$

$$\text{then} (CF = w)$$

Where, A1, A2, $\cdots$ An are propositions, their weighted are w1, w2, $\cdots$ wn, respectively, which are fuzzy numbers defined in the universe of discourse [0,1], and w is also a fuzzy number defined in the universe of discourse [0,1] indicating that the deterministic factor value of the rule R assumes that the propositional truth value, so that the proposition of the fuzzy truth value can be evaluated as follows:

$$CF = T \otimes w \tag{6}$$

Where, $T = A1 \odot w1 \oplus A2 \odot w2 \oplus \cdots \oplus An \odot wn$ or $T = A1 \oslash w1 \oplus A2 \oslash w2 \oplus \cdots \oplus An \oslash wn$, w is a positive fuzzy triangular number.

3.5. Weighted fuzzy forest fire prediction

In this section, we present a technology for forest fire prediction based on weighted fuzzy reasoning process of rule-based systems. The definition of a generalized weighted fuzzy forest fire prediction structure with only two parameters containing temperature and humidity is as follows:

- The temperature is high extremely, which is expressed as a fuzzy triangular number (0.75,1,1)
- w_2=The humidity is low extremely, which is expressed as a fuzzy triangular number (0.75, 1,1), represents the probability of forest fire ignition is extremely high, which is expressed as a fuzzy triangular number(0.75, 1, 1).

Hypothesis, if $w_1 = (0.75, 1, 1)$ and$w_2 = (0.75, 1, 1)$, the probability of forest fire is w = (0.75, 1, 1). Now, we acquire the weather data from a sensor node's station, the temperature and humidity are 20, 60%, respectively. Hence, the triangular fuzzy numbers of temperature and humidity are as follows:

$$A_1 = (0.5, 0.6, 0.75), A_2 = (0.25, 0.3, 0.5)$$

The fuzzification of A1 and A2 based on method 1 $\odot$

$$T_1 = [(0.5, 0.6, 0.75) \otimes (0.75, 1.0, 1.0) \oplus (0.25, 0.3, 0.5) \otimes (0.75, 1.0, 1.0)]$$

$$\odot [(0.75, 1.0, 1.0) \oplus (0.75, 1.0, 1.0) = (0.5625, 0.9, 1.25)$$

$$\odot (1.5, 2, 2) = (0.34, 0.45, 0.625)$$

The fuzzy truth value of possibility of forest fire is calculated.

$$CF^1 = T_1 \otimes w = (0.34, 0.45, 0.625) \otimes (0.75, 1, 1)$$

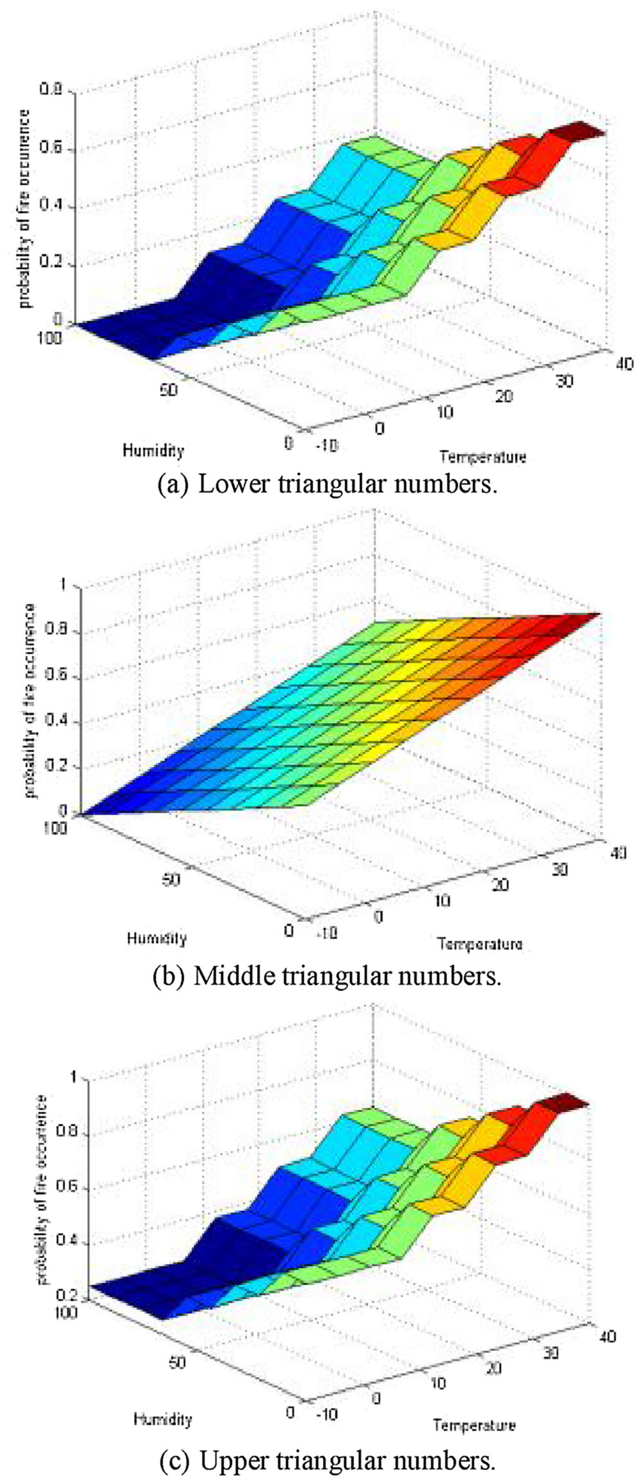


Fig. 7. The fuzzy triangular numbers over temperature and humidity.

$= (0.255, 0.45, 0.625)$

The fuzzification of A1 and A2 based on method 2 $\oslash$

$$T_2 = [(0.5, 0.6, 0.75) \otimes (0.75, 1.0, 1.0) \oplus (0.25, 0.3, 0.5) \otimes (0.75, 1.0, 1.0)]$$

$$\oslash [(0.75, 1.0, 1.0) \oplus (0.75, 1.0, 1.0)] = (0.5125, 0.9, 1.25) \oslash (1.5, 2, 2) = (0.256, 0.45, 0.83)$$

The fuzzy truth value of possibility of forest fire is calculated.

$$CF^2 = T_1 \otimes w = (0.256, 0.45, 0.83) \otimes (0.75, 1, 1) = (0.182, 0.45, 0.83)$$

Fig. 6 shows the triangular fuzzy numbers division of probability of forest fire based on method 1 ($\odot$) and 2 ($\oslash$) varying with fuzzy triangular numbers of temperature and humidity. The curve of triangular fuzzy numbers based on method 2 covers the area of that of method 1 and has a larger stretching, which means it is more difficult to judge the potential of forest fire because of high range result. Therefore, the method 1 is applied in our work for fuzzificaiton of parameters.

Fig. 7 shows the probability of fire occurrence and the surface indicates the probability for different values of temperature and relative humidity used in simulations. Fig. 7(a) shows the diversification of potential of forest fire varying with the lower triangular fuzzy numbers of temperature and humidity. We assume when the temperature reaches 40 °C and the relative humidity reaches 0%, the probability of forest fire will approach 1, which means it is high possible for forest fire occur. While the temperature reaches −10 °C and the relative humidity reaches 100%, the fuzzification result reaches 0. Thus, the real truth of final result will be in this interval [0,1]. Fig. 7(b) and (c) show the middle triangular numbers and upper triangular numbers, respectively.

4. Study Area

The FWI system was applied in Jiangsu Province, China, with high population density and forest fires frequently. Jiangsu Province lies in the southern region of China. The main forest type is a deciduous needle leaved mixed forest contains natural forest and plantation, as is shown in Figs. 8 and 9. The common tree species which may be present are coniferous forest, broad leaf forest, mixed wood and bamboo forest. Even though a low forest coverage rate is considered, the region has a larger population density and better economic conditions. Particularly, the area of plantations increases gradually during the past few years. The forest fires of this region on the rise become more and more frequent. By the end of 2011, the region has 2,174,500 hectares of forest, 1,815,300 hectares of woodland, which covers 21.2% of the land base, and total stumpage is 87 million cubic meters. In Jiangsu Province, the southern region has 459,300 hectares of forest, 23.3% of forest coverage, and total stumpage 14 million cubic meters. Central region has the forest area of 269,600 hectares, the forest coverage rate of 19.3%, total stumpage 7.7 million cubic meters. Northern region has 1,086,400 hectares of forest area, forest coverage of 26.7%, total stumpage 65.3 million cubic meters. There were 51 cases of forest fires in 2011 of Jiangsu Province, a total area of 141.3 hectares burned, 52.4 hectares of forest disappeared. The rate of forest fires was 5.1 per 100,000 hectares, and the victimization rate reaches 0.029/1000.

Nanjing City, the capital of Jiangsu Province, the southern region of China, locates in the northern hemisphere, longitude from 118°22′ to 119°14′, latitude from 31°14′ to 32°37′. It locates in the middle and lower reach of Yangtze River and has a humid subtropical climate with four distinct seasons, and abundant rainfall in summer. The region has annual 117 days with rainfall, an average annual rainfall of 1106.5 mm, relative humidity of 76%, and frost-free period of 237 days. The day lengths of summer are longer than winter.

5. Analyses

5.1. Experiment Setup

In order to evaluate forest fire forecast system based on the fuzzy inference system and big data analysis, we have deployed a large number of sensor nodes and monitoring system in the ZiJin Mountain (Nanjing City, China), which is one of the most famous National Forest Park in China. The mountain area is about 210760 hm2, which is covered by pine needles, pittosporum, camphor, wild chestnut, etc., as shown in Fig. 10. The forest park is located in the center of City, and a considerable number of people visit it each day. In the history, the forest fire is very frequent owing to the carelessness of visitors and dry weather.

In the experiment, each sensor equipped with a solar panel optimized for outdoor use, two eZ430-RF2500T target boards and one AAA battery pack, which is rechargeable and can be recharged repeatedly, as is shown in Fig. 11. The target board comprises the TIMSP430 microcontroller, CC2500 radio transceiver and an on-board antenna. The CC2500 radio transceiver operates in the 2.4 GHz band with data rate of 250 kbps and is designed for low power wireless applications. The harvested energy is stored in EnerChip, a thin-film rechargeable energy storage device with low self-discharge manufactured by Cymbet. We set 100 m as the max communication rage of each sensors. All the sensors have rechargeable power system. Every two sensors can communicate with each other within the range.

The rechargeable wireless sensor network in our experiments is the use of solar energy harvesting, which refers to recharge energy from sun. Sensors are equipped with recharge hardware that can convert solar energy into electricity power. The device of rechargeable system is the energy supplement of battery that is used in traditional WSNs [16,17], which can ensure a sensor node working continually for several years and even more time. Two sensors are deployed in forestry field, as is shown in Fig. 12.

5.2. System Implementation

One of our objectives is to maintain the attainability of the network for as long as possible and collect accurate data as much as possible to support the research on forest fire prevention and detection, which are also demonstrated to be necessary for other applications of sensor networks. Sensor nodes and multiple sinks are deployed in the two places to monitor the coverage area. Most of them are powered by two energy systems, including a rechargeable battery and a common battery together.

Weather data such as temperature, relative humidity, wind speed, rainfall, and day length are collected by the rechargeable wireless sensors as shown in Fig. 12. Sensors forward the data to a remote sensor and finally forward the data to the sink. Our fuzzy prediction algorithm can cover the area of the deployed sensors. In our experiments, the monitored time is from September 1 to November 30 for Nanjing City in 2013.

The Zijin Mountain is a famous sightseeing, and many famous persons were buried in the place. Therefore, in holiday, human are

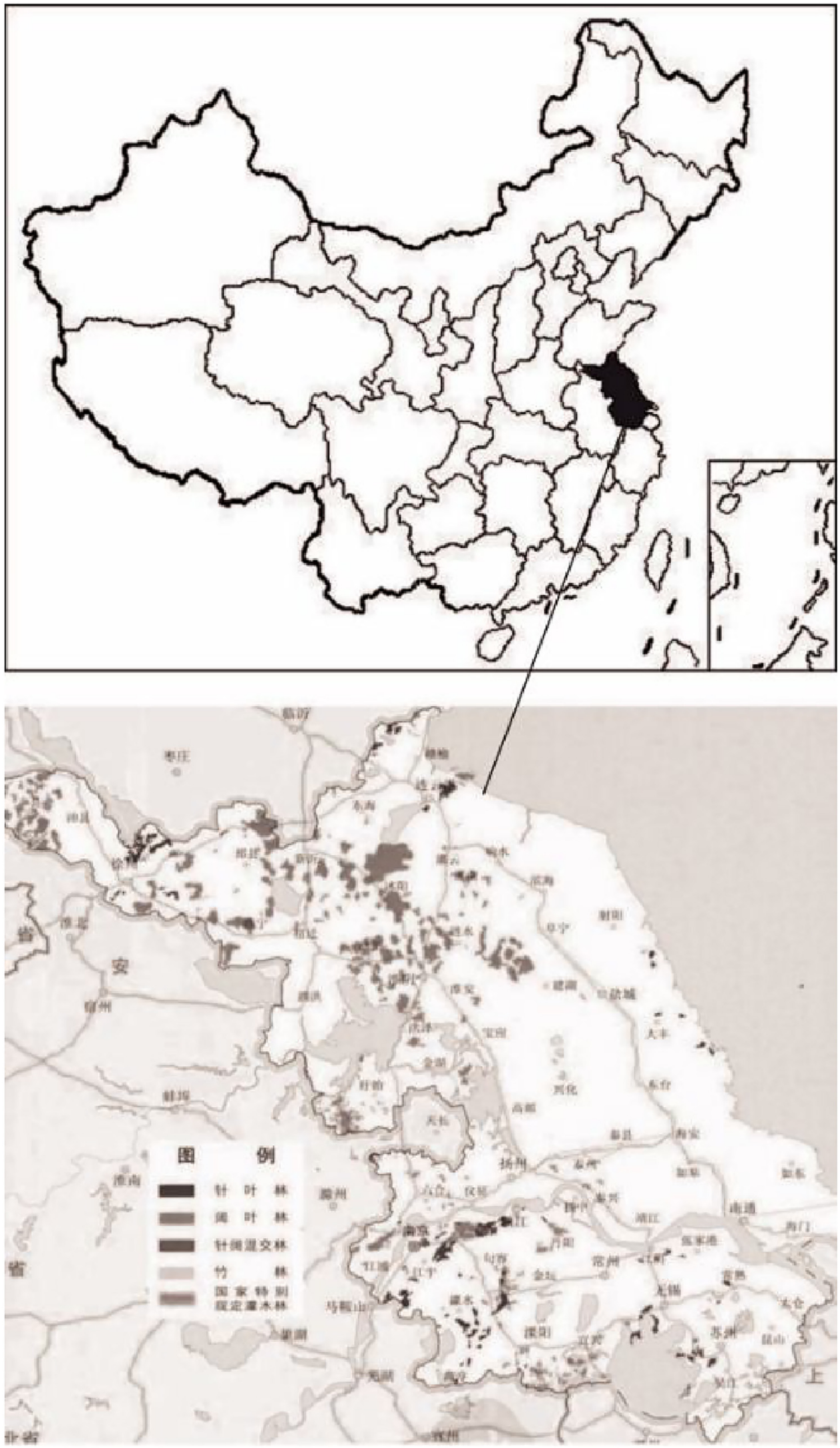


Fig. 8. Location of the Jiangsu Province and the main forest type for natural forest and plantation.

willing to have a visit to the park together with family or friends, such as, Mid-autumn Day and National Day. Mid-autumn Day is a Chinese festival from September 19 to 21 for the year 2013 and National Day from October 1 to 7 for each year. In these days, if it is a sunny day, a larger number of people will visit the forest area, and the potential of human-cause forest fire is higher than

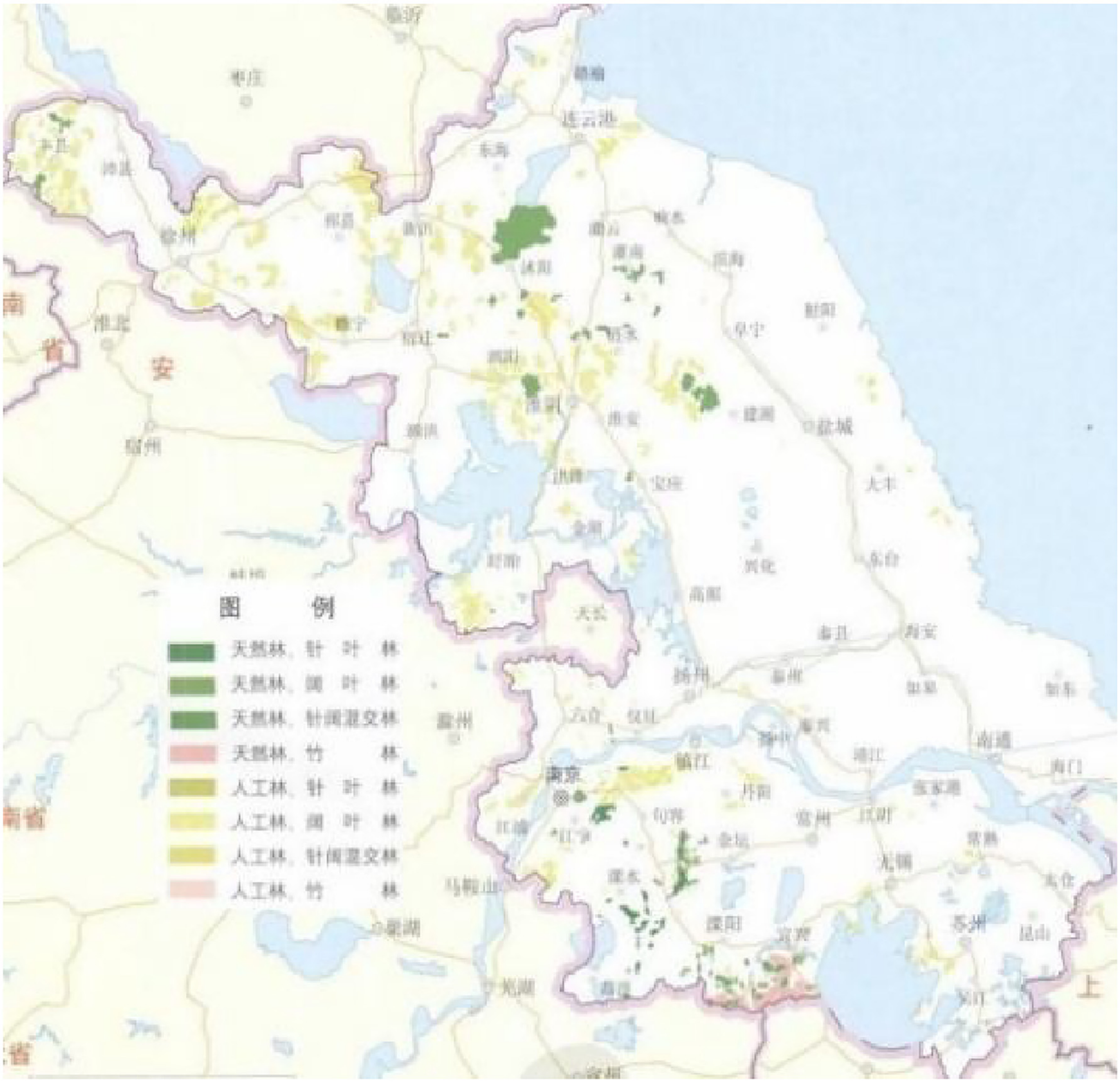


Fig. 9. The main forest type in Jiangsu Province.

working day. For instance, the number of visitors reaches 35,000 on October 1, 2013. Therefore, the forest protection people should pay a special attention to the park in holiday and weekend day. The ignition of forest usually occurs in surround of entrance roads to the forest area. The mainly reasons is that human are willing to go to the park along the entrance way, which leads to a high population density and a higher possibility of forest fire owing to carelessness of visitors. Therefore, the potential of forest fire is affected by road density. More roads and higher population density are easier to cause ignition of forest fire.

The continuous 24 h data of temperature, humidity, speed of wind determine the middle limit of the fuzzy algorithm of forest fire risk is shown in Fig. 13. All the data of weather are collected by the deployed rechargeable wireless sensors in Nanjing from 118°22′ to 119°14′, latitude from 31°14′ to 32°37′. The population number is obtained by a special sensor equipped in an entrance road.

The right, middle and left limit of our fuzzy prediction algorithm is shown in Fig. 14. From Fig. 10, 0.75 is the middle limits of forest fire prediction and we consider it as very high level. We need to pay more attention to those days which have extreme fire danger such as, 9/19/2013, 9/20/2013, 10/1/2013-10/7/2013. These days are holiday and sunny day, so a large number of people will visit the park. At the same time, the temperature is high and relative humidity is low. Therefore, forest fire risk is higher than other days.

More than 80% forest fire occurred either in the spring or in autumn with a slight bimodal distribution, which usually are called fire seasons. It is drier weather conditions in autumn and increased human activities for harvesting of crop. Especially, holiday had the highest fire activity because there is an increase in human activities resulting in many human caused fires.

6. Conclusion

In this paper, we proposed a fuzzy prediction algorithm of forest fire preventing system implemented by rechargeable wireless sensor network. Large scale fire hazards can be dealt with as a strategic planning tool. The system is on the influence among certain fuzzy variables, thus, it can be set to different landmarks of the variables, and prevent potential forest fire.

In the system, more variables than just temperature, humidity can be considered relying on the new technology of WSNs, which can achieve 24-hour monitoring of whether meteorological factors. Finally, we can deploy a reasonable number of sensors to monitor and collect weather data which is the input of our fuzzy prediction

Fig. 10. The ZiJin Mountain of Nanjing City.

Fig. 11. Experiment Site.

Fig. 12. Two sensors are deployed in forestry field.

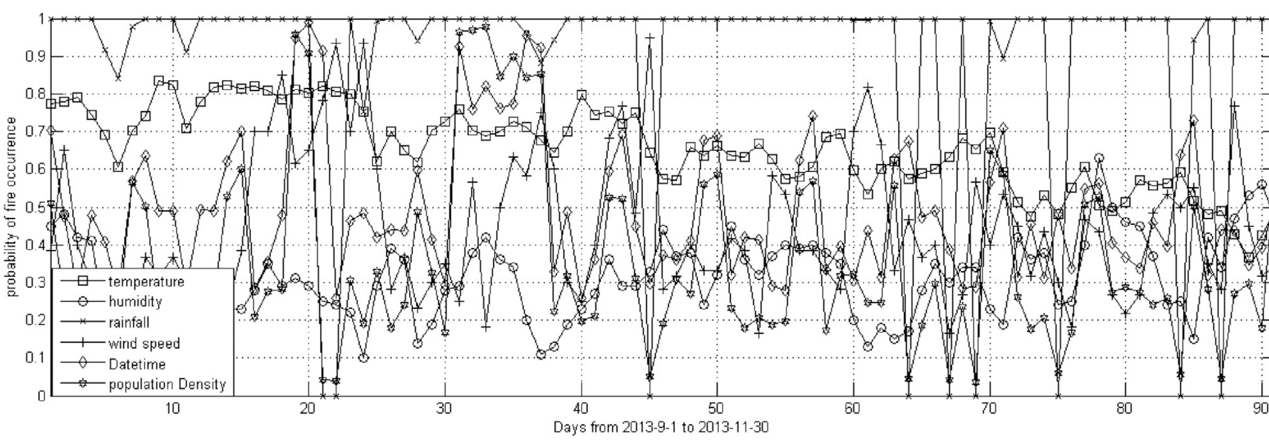


Fig. 13. Probability of forest fire based on the fuzzy reasoning system rely on weather data, datetime and population density.

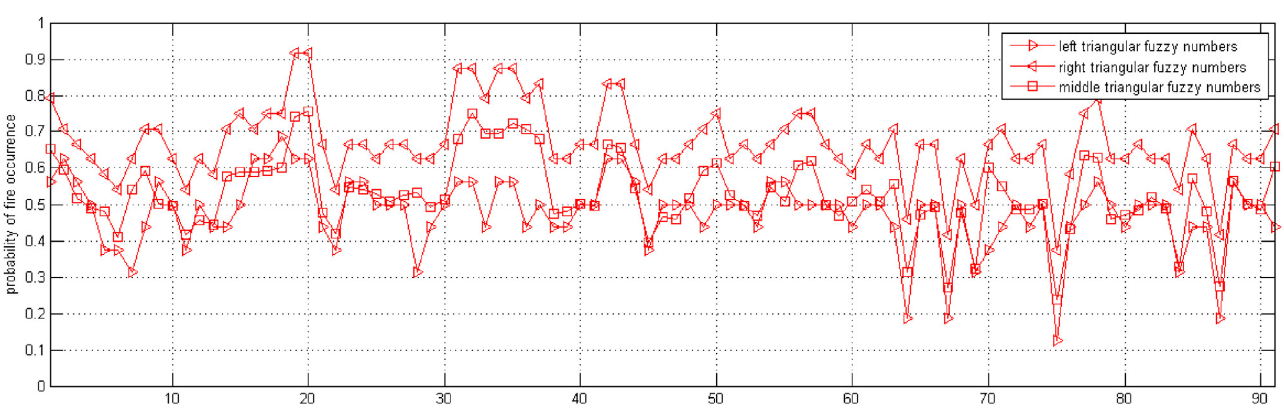


Fig. 14. The left, middle and right limit of the fuzzy triangular based on the fuzzy reasoning system.

algorithm. In terms of forest fire prediction, it is a widely accepted view that relies on a way to be more difficult to predict the occurrence of forest fires accurately.

Acknowledgments

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