Forest Fire Modeling and Early Detection using Wireless Sensor Networks

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Forest fires cost millions of dollars in damages and claim many human lives every year. Apart from preventive measures, early detection and suppression of fires is the only way to minimize the damages and casualties. We present the design and evaluation of a wireless sensor network for early detection of forest fires. We first present the key aspects in modeling forest fires. We do this by analyzing the Fire Weather Index (FWI) System, and show how its different components can be used in designing efficient fire detection systems. The FWI System is one of the most comprehensive forest fire danger rating systems in North America, and it is backed by several decades of forestry research. The analysis of the FWI System could be of interest in its own right to researchers working in the sensor network area and to sensor manufacturers who can optimize the communication and sensing modules of their products to better fit forest fire detection systems. Then, we model the forest fire detection problem as a coverage problem in wireless sensor networks, and we present a distributed algorithm to solve it. In addition, we show how our algorithm can achieve various coverage degrees at different subareas of the forest, which can be used to provide unequal monitoring quality of forest zones. Unequal monitoring is important to protect residential and industrial neighborhoods close to forests. Finally, we present a simple data aggregation scheme based on the FWI System. This data aggregation scheme significantly prolongs the network lifetime, because it only delivers the data that is of interest to the application. We validate several aspects of our design using simulation.

Categories and Subject Descriptors: H.4.0 [**Information Systems**]: Information Systems Applications—*General*; C.3 [**Computer Systems Organization**]: Special-Purpose and Application-Based Systems

General Terms: Design, Algorithms

Additional Key Words and Phrases: Forest Fire Modeling, Forest Fire Detection Systems, Wireless Sensor Networks, Coverage Protocols

1. INTRODUCTION

Forest fires, also known as wild fires, are uncontrolled fires occurring in wild areas and cause significant damage to natural and human resources. Forest fires eradicate forests, burn the infrastructure, and may result in high human death toll near urban areas. Common causes of forest fires include lightning, human carelessness, and exposure of fuel to extreme heat and aridity. It is known that in some cases fires are part of the forest ecosystem and they are important to the life cycle of indigenous habitats. However, in most cases, the damage caused by fires to public safety and natural resources is intolerable and early detection and suppression of fires deem crucial. For example, in August 2003, a forest fire was started by a lightning strike in the Okanagan Mountain Park in the Province of British Columbia, Canada. The fire was spread by the strong wind and within a few days it turned into a firestorm. The fire forced the evacuation of 45,000 residents and burned 239 homes. Most of the trees in the Okanagan Mountain Park were burned, and the park was closed. Although 60 fire departments, 1,400 armed forces troops and 1,000 fire fighters took part in the fire fighting operation, they were largely unsuccessful in stopping the disaster. The official reports estimate the burned area as 25,912 hectares and the total cost as $33.8 mil-

Table I. Forest fires in the Province of British Columbia, Canada since 1995.

Year	Number of Fires	Number of Hectares Burned	Total Cost (millions)
2006	2,590	131,086	$156.0
2005	976	34,588	$47.2
2004	2394	220,516	$164.6
2003	2473	265,050	$371.9
2002	1783	8,539	$37.5
2001	1266	9,677	$53.8
2000	1539	17,673	$52.7
1999	1208	11,581	$21.1
1998	2665	76,574	$153.9
1997	1175	2,960	$19.0
1996	1358	20,669	$37.1
1995	1474	48,080	$38.5

lion [B.C. Ministry of Forests and Range]. In the province of British Columbia alone, there have been 2,590 forest fires during 2006 [B.C. Ministry of Forests and Range Web Page]. These burned 131,086 hectares and costed about $156 million. Table I summarizes the extent and cost of wild fires in BC in previous years. The situation of forest fires is even worse if we look at the national level. Over the past ten years, on average, there have been 4,387 and 52,943 forest fires in Canada and the United States, respectively, per year [Canadian Forest Service (CFS) Web Page]. Preventing a small fraction of these fires would account to significant savings in natural and human resources.

Apart from preventive measures, early detection and suppression of fires is the only way to minimize the damage and casualties. Systems for early detection of forest fires have evolved over the past decades based on advances in related technologies. We summarize this evolution in the following, motivating the need and potential of wireless sensor networks for this critical application.

1.1 Evolution of Forest Fire Detection Systems

Traditionally, forest fires have been detected using fire lookout towers located at high points. A fire lookout tower houses a person whose duty is to look for fires using special devices such as Osborne fire finder [Fleming and Robertson 2003]. Osborne fire finder is comprised of a topographic map printed on a disk with graduated rim. A pointer aimed at the fire determines the location and the direction of the fire. Once the fire location is determined, the fire lookout alerts fire fighting crew. Fire lookout towers are still in use in many countries around the world including USA, Australia, and Canada [B.C. Fire Lookout Towers].

Unreliability of human observations in addition to the difficult life conditions for fire lookout personnel have led to the development of automatic video surveillance systems [Fire Watch Web Page ; Breejen et al. 1998; Khrt et al. 2001]. Most systems use Charge-Coupled Device (CCD) cameras and Infrared (IR) detectors installed on top of towers. CCD cameras use image sensors which contain an array of light sensitive capacitors or photodiodes. In case of fire or smoke activity, the system alerts local fire departments, residents, and industries. Current automatic video surveillance systems used in Germany, Canada, and Russia are capable of scanning a circular range of 10 km in less than 8 minutes [Fire Watch Web Page]. The accuracy of these systems is largely affected by weather conditions such as clouds, light reflection, and smoke from industrial activities. Automatic video surveillance systems cannot be applied to large forest fields easily and cost effectively, thus for large forest areas either aeroplanes or Unmanned Aerial Vehicles (UAV) are used to monitor forests. Aeroplanes fly over forests and the pilot alerts the base station in case of fire or smoke activity. UAVs, on the other hand, carry both video and infrared cameras and transmit the collected data to a base station on the ground that could be up to 50 km away. UAVs can stay atop for several hours and are commanded by programming or joystick controls [Aerovision Web Page].

More advanced forest fire detection systems are based on satellite imagery. Advanced Very High Resolution Radiometer (AVHRR) [AVHRR Web Page] was launched by National Oceanic and Atmospheric Administration (NOAA) in 1998 to monitor clouds and thermal emission of the Earth. Moderate Resolution Imaging Spectroradiometer (MODIS) [MODIS Web Page] was launched by NASA in 1999 on board of the Aqua satellite to capture cloud dynamics and surface radiation from the Earth. Current satellite-based forest fire detection systems use data from these instruments for forest fire surveillance. The instruments provide a complete image of the Earth every 1 to 2 days. The minimum detectable fire size is 0.1 hectare, and the fire location accuracy is 1 km [L et al. 2000; Lohi et al. 1999]. The accuracy and reliability of satellite-based systems are largely impacted by weather conditions. Clouds and rain absorb parts of the frequency spectrum and reduce spectral resolution of satellite imagery which consequently affects the detection accuracy. Although satellite-based systems can monitor a large area, relatively low resolution of satellite imagery means a fire can be detected only after it has grown large. More importantly, the long scan period—which can be as long as 2 days—indicates that such systems cannot provide timely detection.

To summarize, the most critical issue in a forest fire detection system is immediate response in order to minimize the scale of the disaster. This requires constant surveillance of the forest area. Current medium and large-scale fire surveillance systems do not accomplish timely detection due to low resolution and long period of scan. Therefore, there is a need for a scalable solution that can provide real time fire detection with high accuracy. We believe that wireless sensor networks (WSN) can potentially provide such solution.

Recent advances in WSN support our belief that they make a promising framework for building near real-time forest fire detection systems. Currently sensing modules can sense a variety of phenomena including temperature, relative humidity, and smoke [Crossbow Inc. Web Page] which are all helpful for fire detection systems. Sensor nodes can operate for months on a pair of AA batteries to provide constant monitoring during the fire season. Moreover, recent protocols make sensor nodes capable of organizing themselves into a self-configuring network, thus removing the overhead of manual setup. Large-scale wireless sensor networks can be easily deployed using aeroplanes at a low cost compared to the damages and loss of properties caused by forest fires.

1.2 Contributions and Paper Organization

In this paper, we present the design and evaluation of a wireless sensor network for early detection of forest fires. Our design is based on solid forestry research conducted by the Canadian Forest Service [Canadian Forest Service (CFS) Web Page] over several decades. In particular our contributions can be summarized as follows:

—We present the key aspects in modeling forest fires. We describe the Fire Weather Index System [Canadian Forest Service (CFS) Web Page ; de Groot 1998], and show how its different components can be used in designing efficient fire detection systems. This could be of interest to researchers working in this area and to sensor manufacturers who can optimize the communication and sensing modules of sensors to fit forest fire detection systems.

—We model the forest fire detection problem as a k-coverage problem ($k \geq 1$) in wireless sensor networks, and present a distributed algorithm to solve this problem.

—We present a simple data aggregation scheme based on the FWI System, which significantly prolongs the network lifetime.

—We show how our k-coverage algorithm can be extended to address several issues relevant to forest fire detection systems, such as providing different coverage degrees at different subareas of the forest. This is important because, for example, the parts of the forest that are near residential areas need to be monitored with higher accuracy than others.

The rest of the paper is organized as follows. In Sec. 2, we summarize the related work. Sec. 3 describes the FWI System which is the basis of our design. The details of our design are presented in Sec. 4. In Sec. 5, we evaluate various aspects of the proposed system, and we conclude the paper in Sec. 6.

2. RELATED WORK

Sensor networks have several appealing characteristics for environmental monitoring applications such as habitat monitoring [Mainwaring et al. 2002; Akyildiz et al. 2002], and forest fire detection systems [Son et al. 2006; Yu et al. 2005; Doolin and Sitar 2005; Chaczko and Ahmad 2005].

For example, in [Mainwaring et al. 2002], the authors apply wireless sensor networks to habitat monitoring. A set of system requirements are developed and a system architecture is proposed to address these requirements. Different issues such as deployment, data collection, and communication protocols are discussed and design guidelines are provided. The system is comprised of patches of sensor nodes reporting their readings to a base station through gateway nodes. The base station is connected to the Internet and exposes the collected data to a set of web-based applications. They present experimental results from a habitat monitoring system consisting of 32 nodes deployed on a small island off the coast of Maine. The sensors were placed in burrows to collect temperature data which are used to detect the presence of nesting birds.

The authors of [Doolin and Sitar 2005] show the feasibility of wireless sensor networks for forest fire monitoring. Experimental results are reported from two controlled fires in San Francisco, California. The system is composed of 10 GPS-enabled MICA motes [Crossbow Inc. Web Page] collecting temperature, humidity, and barometric pressure data. The data is communicated to a base station which records it in a database and provides services for different applications. The experiments show that most of the motes in the burned area were capable of reporting the passage of the flame before being burned. In contrast to this system which reports raw weather data, our design processes weather conditions based on the Fire Weather Index System [Canadian Forest Fire Danger Rating System (CFFDRS) Web Page] and reports more useful, summarized, fire indexes.

In [Hartung et al. 2006], the authors address the problem of fire behavior study rather than fire detection. They present FireWxNet, a portable fire sensor network to measure the

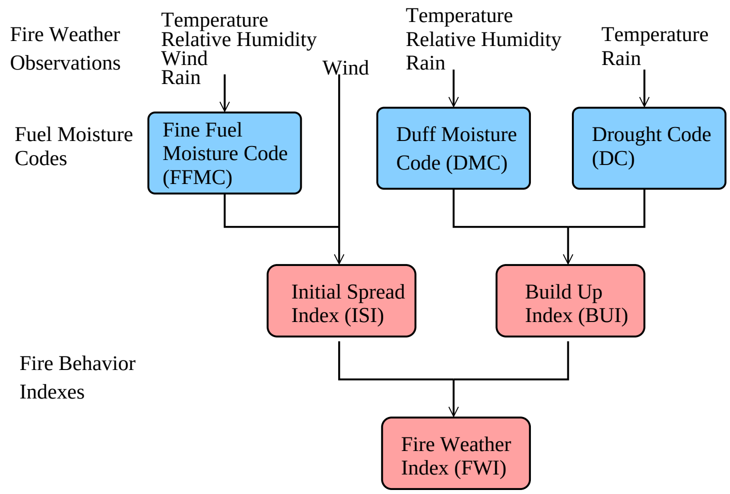


Fig. 1. Structure of the Fire Weather Index (FWI) System.

weather conditions surrounding active fires. The system is comprised of sensor nodes, webcams, and base stations which are capable of long distance communication. FireWxNet is deployed at the fire site to study the fire behavior using the collected weather data and visual images. Temperature, relative humidity, wind speed and direction are collected every half an hour while cameras provide a continuous view of the current fire condition. The experimental results indicate that the system is capable of providing useful data for fire behavior analysis. Our system is designed for a different application which is early detection of forest fires.

A Forest fire Surveillance System for South Korea mountains is designed in [Son et al. 2006]. The authors provide a general structure for sensor networks and provide details for a forest fire detection application. The sensor types, operating system and routing protocol are discussed. Sensor nodes use a minimum cost path forwarding to send their readings to a sink which is connected to the Internet. The data is reported to a middleware which calculates the forest fire risk level according to formulas defined by forestry service. The calculation is depending on daily measurement of relative humidity, precipitation, and solar radiation. The results are recorded in a database that can be accessed by web applications over the Internet. Instead of using a middleware, we propose calculating fire indexes according to the FWI System at cell heads where the data is more likely to be correlated. This removes the need for communicating all sensor data to the sink. Instead only a few aggregated indexes are reported to reduce energy consumption.

3. UNDERSTANDING AND MODELING FOREST FIRES

Forests cover large areas of the earth and are often home to many animal and plant species. They function as soil conserver and play an important role in the carbon dioxide cycle. To assess the possibility of fires starting in forests and rate by which they spread, we adopt one of the most comprehensive forest fire danger rating systems in North America. We use the Fire Weather Index (FWI) System developed by the Canadian Forest Service (CFS)[Canadian Forest Service (CFS) Web Page], which is based on several decades of

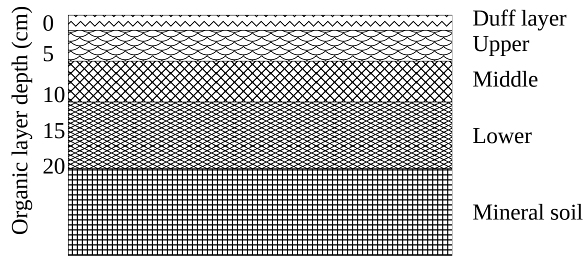


Fig. 2. Forest soil layers.

forestry research [San-Miguel-Ayanz et al. 2003].

The FWI System estimates the moisture content of three different fuel classes using weather observations. These estimates are then used to generate a set of indicators showing fire ignition potential, fire intensity, and fuel consumption. The daily observations include temperature, relative humidity, wind speed, and 24-hour accumulated precipitation, all recorded at noon Local Standard Time (LST). The system predicts the peak fire danger potential at 4:00 pm LST. Air temperature influences the drying of fuels and thus affects the heating of fuels to ignition temperature. Relative humidity shows the amount of moisture in the air. Effectively, a higher value means slower drying of fuels since fuels will absorb moisture from the air. Wind speed is an important factor in determining fire spread for two main reasons: (a) it controls combustion by affecting the rate of oxygen supply to the burning fuel, and (b) it tilts the flames forward, causing the unburned fuel to be heated [Pearce 2000]. The last factor, precipitation, plays an important role in wetting fuels.

As shown in Fig. 1, the FWI System is comprised of six components: three fuel codes and three fire indexes. The three fuel codes represent the moisture content of the organic soil layers of forest floor, whereas the three fire indexes describe the behavior of fire. In the following two sections, we briefly describe these codes and indexes. In Section 3.3, we present how these codes and indexes can be interpreted and utilized in designing a wireless sensor network for early forest fire detection.

3.1 Fuel Codes of the FWI System

The forest soil can be divided into five different layers [Canadian Forest Service (CFS) Web Page ; de Groot 1998] as shown in Fig. 2. Each layer has specific characteristics and provides different types of *fuels* for forest fires. These characteristics are reflected in fuel codes of the FWI System. Related to each fuel type, there is a drying rate at which the fuel loses moisture. This drying rate, called timelag, is the time required for the fuel to lose two-thirds of its moisture content with a noon temperature reading of 21°C, relative humidity of 45%, and a wind speed of 13 km/h [de Groot 1998]. Also, each fuel type has a fuel loading metric, which describes the average amount (in tonnes) of that fuel which exists per hectare.

There are three fuel codes in the FWI System: Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), and Drought Code (DC). FFMC represents the moisture content of litter and fine fuels, 1–2 cm deep, with a typical fuel loading of about 5 tonnes per hectare. The timelag for FFMC fuels is 16 hours. Since fires usually start and spread in fine fuels[de Groot 1998], FFMC can be used to indicate ease of ignition, or ignition probability.

Table II. Ignition Potential versus the FFMC value.

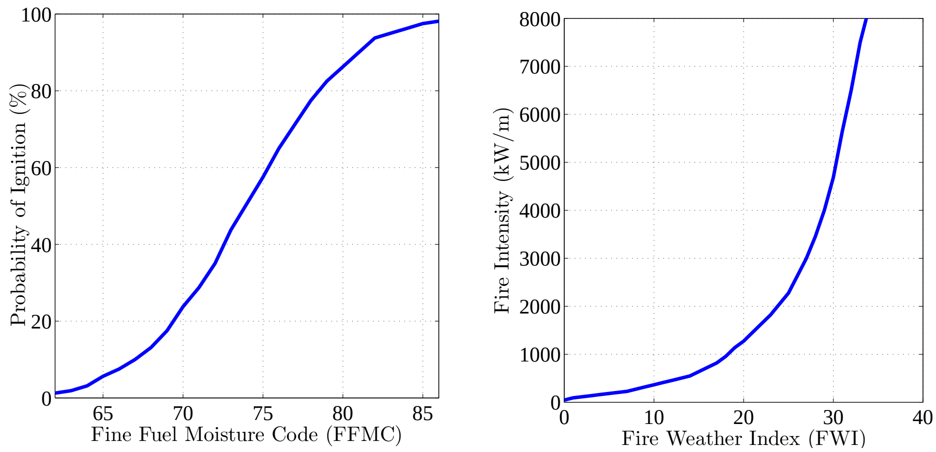
Ignition Potential	FFMC Value Range
Low	0–76
Moderate	77–84
High	85–88
Very High	89–91
Extreme	92+

The Duff Moisture Code (DMC) represents the moisture content of loosely compacted, decomposing organic matter, 5–10 cm deep, with a fuel loading of about 50 tonnes per hectare. DMC is affected by precipitation, temperature and relative humidity. Because these fuels are below the forest floor surface, wind speed does not affect the fuel moisture content. DMC fuels have a slower drying rate than FFMC fuels, with a timelag of 12 days. Although the DMC has an open-ended scale, the highest probable value is about 150[de Groot 1998]. The DMC determines the probability of fire ignition due to lightning and also shows the rate of fuel consumption in moderate depth layers. The last fuel moisture code, the Drought Code (DC), is an indicator of the moisture content of the deep layer of compacted organic matter, 10–20 cm deep, with a fuel loading of about 440 tonnes per hectare. Temperature and precipitation affect the DC, but wind speed and relative humidity do not have any effect on it due to the depth of this fuel layer. DC fuels have a very slow drying rate, with a timelag of 52 days. The DC is indicative of long-term moisture conditions, determines fire's resistance to extinguishing, and indicates fuel consumption in deep layers. The DC scale is also open-ended, although the maximum probable value is about 800[de Groot 1998].

3.2 Fire Indexes of the FWI System

Fire indexes of the FWI System describe the spread and intensity of fires. There are three fire indexes: Initial Spread Index (ISI), Buildup Index (BUI), and Fire Weather Index (FWI). As indicated by Fig. 1, ISI and BUI are intermediate indexes and are used to compute the FWI index. The ISI index indicates the rate of fire spread immediately after ignition. It combines the FFMC and wind speed to predict the expected rate of fire spread. Generally, a 13 km/h increase in wind speed will double the ISI value. The BUI index is a weighted combination of the DMC and DC codes, and it indicates the total amount of fuel available for combustion. The DMC code has the most influence on the BUI value. For example, a DMC value of zero always results in a BUI value of zero regardless of what the DC value is. DC has its strongest influence on the BUI at high DMC values, and the greatest effect that the DC can have is to make the BUI value equal to twice the DMC value.

The Fire Weather Index (FWI) is calculated from the ISI and BUI to provide an estimate of the intensity of a spreading fire. In effect, FWI indicates fire intensity by combining the rate of fire spread with the amount of fuel being consumed. Fire intensity is defined as the energy output measured in kilowatts per meter of flame length at the head of a fire. The head of a fire is the portion of a fire edge showing the greatest rate of spread and fire intensity. The FWI index is useful for determining fire suppression requirements as well as being used for general public information about fire danger conditions. Although FWI is not directly calculated from weather data, it depends on those factors through ISI and BUI.



(a) Probability of ignition as a function of the FFMC code

(b) Fire intensity as a function of the FWI index

Fig. 3. Using two main components of the Fire Weather Index System in designing a wireless sensor network to detect and combat forest fires.

3.3 Interpreting and Using the FWI System

There are two goals of the proposed wireless sensor network for forest fires: (i) provide early warning of a potential forest fire, and (ii) estimate the scale and intensity of the fire if it materializes. Both goals are needed to decide on required measures to combat a forest fire. To achieve these goals, we design our sensor network based on the two main components of the FWI System: (i) the Fine Fuel Moisture Code (FFMC), and (ii) the Fire Weather Index (FWI). The FFMC code is used to achieve the first goal and the FWI index is used to achieve the second. In the following, we justify the choice of these two components by collecting and analyzing data from several forestry research publications.

The FFMC indicates the relative ease of ignition and flammability of fine fuels due to exposure to extreme heat. To show this, we interpolate data from [de Groot 1998] to plot the probability of ignition as a function of FFMC. The results are shown in Fig. 3(a). The FFMC scale ranges from 0–101 and is the only component of the FWI System without an open-ended scale. Generally, fires begin to ignite at FFMC values around 70, and the maximum probable value that will ever be achieved is 96 [de Groot 1998]. Based on data available from the web site of The Sustainable Resource Development Ministry of the Province of Alberta, Canada, we classify in Table II the potential of fire ignition versus the FFMC ranges. Low values of FFMC are not likely to be fires and can be simply ignored, while larger values indicate more alarming situations.

The FWI index estimates the fire intensity by combining the rate of fire spread (from the Initial Spread Index, ISI) with the amount of fuel being consumed (from the Buildup Index, BUI). A high value of the FWI index indicates that in case of fire ignition, the fire would be difficult to control. This intuition is backed up by several studies. For example, in 1974, the Alberta Forest Service performed a short term study of experimental burning in the Jack pine forests in north eastern Alberta. Snapshots of the resulting fires and the computed FWI indexes are shown in Fig. 4 for three fires with different FWI values [Alexander and

(a) Moderate surface fire (FWI = 14) (b) Very intense surface fire (FWI = 24) (c) Developing active fire (FWI = 34)

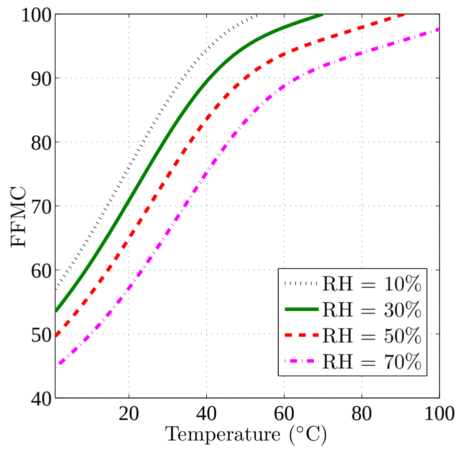
Fig. 4. Experimental validation of the FWI index. Pictures shown from experiments conducted by the Alberta Forest Service, and are reproduced with permission.

Table III. Potential Fire Danger versus the FWI value.

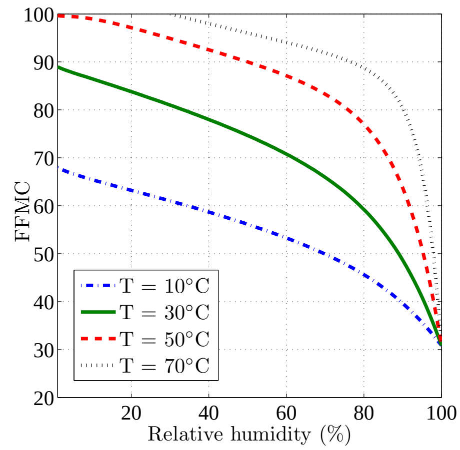
FWI Class	Value Range	Type of Fire	Potential Danger
Low	0–5	Creeping surface fire	Fire will be self extinguishing
Moderate	5–10	Low vigor surface fire	Easily suppressed with hand tools
High	10–20	Moderately vigorous surface fire	Power pumps and hoses are needed
Very High	20–30	Very intense surface fire	Difficult to control
Extreme	30+	Developing active fire	Immediate and strong action is critical

Groot 1988], we obtained a permission to reproduce these images. Another study [de Groot 1998] relates the fire intensity with the FWI index. We plot this relationship in Fig. 3(b) by interpolating data from [de Groot 1998]. In Table III, we provide a classification of fire danger as a function of the FWI index based on the data available from [Canadian Forest Service (CFS) Web Page].

Both the FFMC code and the FWI index are computed from four basic weather conditions: temperature, relative humidity, precipitation, and wind speed. These weather conditions can be measured by sensors deployed in the forest. The accuracy and the distribution of the sensors impact the accuracy of the FFMC code and the FWI index. Therefore, we need to quantify the impact of these weather conditions on FFMC and FWI. Using this quantification, we can design our wireless sensor network to produce the desired accuracy in FFMC and FWI. In addition, this quantification could help other researchers and sensor manufacturers to customize or develop new products that are more suitable for the forest fire detection application. To do this quantification, we contacted the Canadian Forest Service to obtain the closed-form equations that describe the dependence of FFMC and FWI on the weather conditions. We were given access to these equations as well as a program that computes them [Wagner and Pickett 1985], we post an electronic copy of this report at [Network Systems Lab Web Page] for interested researchers in this area. We studied the sensitivity of FFMC and FWI to air temperature and relative humidity. Sample of our results are shown in Fig. 5 and Fig. 6. The sensitivity of FFMC to temperature and relative humidity is shown in Fig. 5 for fixed wind speed at 5 km/h and precipitation level of 5 mm. Fig. 6 shows the sensitivity of FWI to temperature and relative humidity under similar conditions. An interesting observation for sensor manufacturers is that the accuracy of

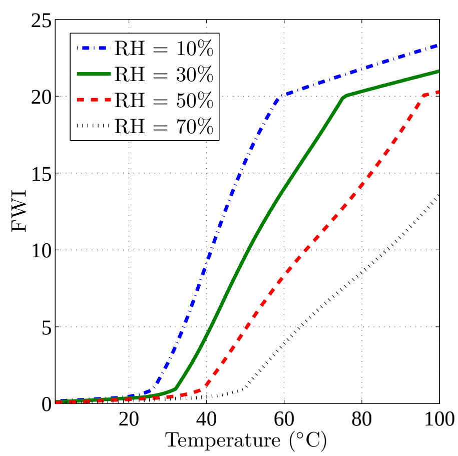


(a) FFMC versus Temperature

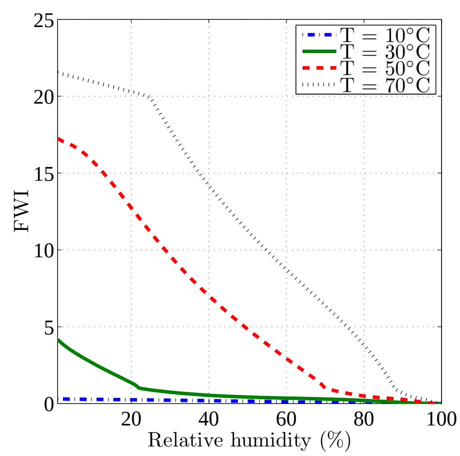


(b) FFMC versus Humidity

Fig. 5. Sensitivity of the FFMC code to basic weather conditions.



(a) FWI versus Temperature



(b) FWI versus Humidity

Fig. 6. Sensitivity of the FWI Index to basic weather conditions.

the sensor readings is critical in high temperature ranges and when humidity is low, while fine accuracy is not that important outside these ranges. We will use these figures to bound the errors in estimating FFMC and FWI in the next section.

In summary, the FFMC code and FWI index provide quantifiable means to detect and respond to forest fires. Low values of FFMC are not likely to be fires and may be ignored. In case of higher FFMC values, where a fire is possible, based on the values of FWI, some fires might be left to burn, some should be contained and others need to be extinguished immediately. We design our wireless sensor network for forest fire detection based on the FFMC code and FWI index. Our system uses weather data collected by sensor nodes to

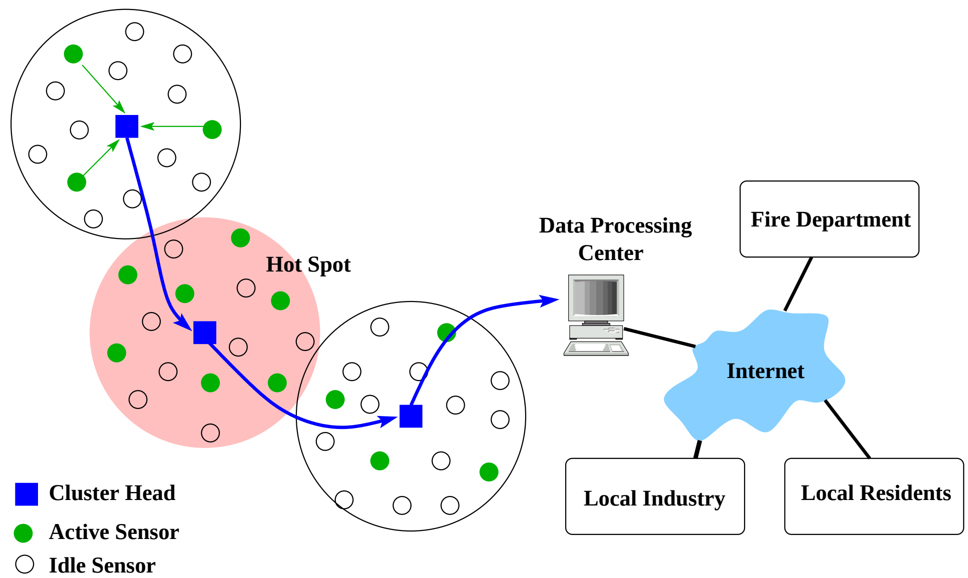


Fig. 7. The architecture of the proposed forest fire detection system. Nodes self-organize into clusters, where cluster heads aggregate collected data using the FWI System. The shaded area represents a forest zone with higher fire potential and thus needs higher monitoring accuracy.

calculate these indexes.

4. EARLY DETECTION OF FOREST FIRES USING WIRELESS SENSOR NETWORKS

In this section, we present the design of a wireless sensor network for forest fire detection. Indeed there are many research problems in such large-scale sensor network. We focus on a subset of them, and we leverage solutions for other problems in the literature, as outlined below.

The system considered in this paper is depicted in Fig. 7. A sensor network deployed in a forest reports its data to a processing center for possible actions, such as alerting local residents and dispatching fire fighting crews. Sensors are deployed uniformly at random in the forest by, for example, throwing them from an aircraft. A single forest fire season is approximately six months (between April and October), and it is desired that the sensor network lasts for several seasons. Since the lifetime of sensors in active mode is much shorter than even a fraction of one season, sensor deployment is assumed to be relatively dense such that each sensor is active only during a short period of time and the monitoring task is rotated among all sensors to achieve the target network lifetime. Therefore, during the network operation, a small fraction of the deployed sensors are kept in *active* mode, while the rest are put in *sleep* mode to conserve energy. It is important to mention that the forest fire detection application considered in this paper works on a large time scale. Thus, active sensors are not continuously monitoring the area. Rather, they periodically (e.g., every 30 minutes) perform the sensing task. Therefore, sensors in the active mode are further divided into *active-sense* and *active-listen* modes. In the former, all modules (transmission, receiving, and sensing) of the sensor are turned on, while in the latter only the receiving module is on.

Sensors are assumed to self-organize into clusters using a distributed protocol. After the termination of the clustering protocol, sensors know their cluster heads and the whole network is connected. Any of the protocols described in the recent survey in [Younis et al. 2006] can be employed. Our proposed system does not restrict the cluster size, and it allows single- and multi-hop intra-cluster communications. The sensor clustering and data routing problems are outside the scope of this paper. We consider four problems in this paper. First, modeling the forest fire detection application as a coverage problem in wireless sensor networks, which we describe in Sec. 4.1. Second, designing a distributed coverage protocol, presented in Sec. 4.2. Third, developing a data aggregation scheme that is suitable for the forest fire detection application, presented in Sec. 4.3. The final problem is achieving unequal fire protection in different zones in the forest, e.g., forest zones near industrial plants and residential areas, or forest zones with drier conditions and higher temperatures (denoted by hot spots). This is illustrated in Fig. 7 by activating more sensors in the shaded hot spot area. We make the case for this unequal protection using real data and present a method to achieve it in Sec. 4.4.

4.1 Modeling Forest Fire Detection as a Coverage Problem

We discussed in the previous section the relevance and importance of the FWI System, especially its FFMC and FWI components. We design our wireless sensor network for forest fire detection based on the FWI System. As shown in Fig. 7, the deployed sensors are grouped into clusters, and each cluster elects a cluster head. Each cluster head periodically computes the FFMC and FWI for its cluster by sampling weather conditions from active sensors inside the cluster. This information is then forwarded—through multi hop routing—to a processing center for possible actions. Recall that FFMC and FWI are computed from basic weather conditions such as temperature and humidity (see Fig. 1).

To be useful in detecting fires and assessing their intensity, FFMC and FWI need to be estimated within specific error bounds. For example, if the error in the estimated FWI is high (e.g. 5 units), the fire would be misclassified as indicated by Table III. To achieve the desired accuracy in FFMC and FWI, basic weather conditions should, in turn, be measured accurately. The accuracy level of measuring basic weather conditions is determined from the curves relating FWI and FFMC to weather conditions, such as Figs. 5 and 6. For instance, the worst-case slope of the FWI-Temperature curve in Fig. 6(a) at RH = 10% is about 0.62. Thus, an error up to 1 unit in FWI requires measuring the temperature with 1.6 degree accuracy. Knowing the needed accuracy in measuring weather conditions, the sensor network should be designed to collect data with that accuracy. We illustrate this design using temperature as an example, the same can be done for other metrics.

Consider measuring the temperature in an arbitrary cluster. Sensors in the cluster should be activated in a way that the samples reported by them represent the temperature in the whole cluster. This means that the cluster area should be covered by the sensing ranges of active sensors. This is called 1-coverage, or coverage with degree 1, because each point in the area is supposed to be within the sensing range of at least one sensor. In dense sensor networks and when sensors are deployed uniformly at random in the area—which is the case for forest fire detection systems as described above—area coverage can be approximated by sensor location coverage [Yang et al. 2006]. That is, we need to activate a subset of sensors to ensure that the locations of all sensors are 1-covered.

In real forest environments, sensor readings may not be accurate due to several factors, including: (i) different environment conditions (e.g., some sensors happen to be in the shade of trees, while others are not), (ii) inaccurate calibration of sensors, (iii) aging of sensors, and (iv) unequal battery levels in sensors. In addition, to cover large forests, sensing ranges of deployed sensors will have to be large (in order of hundreds of meters), which may introduce more errors in the sensor readings. Therefore, multiple (k) samples may be needed to estimate the temperature at a location with the target accuracy. That is, each location needs to be sensed by k different sensors. This is called k-coverage, where $k \geq 1$. The actual value of k depends on the expected error in the sensor readings and the tolerable error in the FFMC and FWI indexes. One way to estimate k is described in the following.

We define a random variable T as the reading of a sensor inside the cluster. It is reasonable to assume that T follows a normal distribution because of the many factors contributing to it, which all are naturally stochastic. We denote the mean and standard deviation of T as μ_T and σ_T, respectively. The estimated mean $\widehat{\mu}_T$, also known as the sample mean, is given by: $\widehat{\mu}_T = \frac{1}{k}\sum_{i=1}^{k} t_i$, where t_is are the individual sensor readings, and k is the number of samples. As the number of samples increases, the sample mean becomes closer to the actual mean. The error between the sample mean and the population mean, $\delta_T = |\mu_T - \widehat{\mu}_T|$, is calculated as follows [Taylor 1997]: $\delta_T = z_{\frac{\alpha}{2}} \dfrac{\sigma_T}{\sqrt{k}}$, where z is the standard normal distribution, α is the length of the confidence interval, σ_T is the population standard deviation, and k is the sample size. $z_{\frac{\alpha}{2}}$ can be obtained from tables of the standard normal distribution. Rearranging the formula, we get:

$$k = \left\lceil (z_{\frac{\alpha}{2}} \frac{\sigma_T}{\delta_T})^2 \right\rceil. \tag{1}$$

Thus, given a confidence value of $100(1-\alpha)\%$ and standard deviation of σ_T, we can determine the sample size required to estimate the population mean μ_T within δ_T error margin. σ_T can be calculated from the specifications of the sensing board. The error in sensor measurements is usually interpreted as $2\sigma_T$. To illustrate, suppose we want to measure the temperature with a maximum error of $1°$C and with a confidence value of 95%. Assume that sensors have temperature sensing boards with an error up to $2°$C, i.e., $\sigma_T = 1$. Therefore, we need a coverage degree $k = (1.96 \times 1/1)^2 = 4$. In the evaluation section, we study and validate the relationship between the coverage degree k and the error in FFMC and FWI. We also study the tradeoff between the error in the sensor readings σ_T and the required coverage degree k to meet given target errors in FFMC and FWI.

To summarize, in this section we have established a mapping between the forest fire detection system and the k-coverage problem ($k \geq 1$) in sensor networks. We showed how k can be estimated based on the error in sensor readings and the maximum tolerable errors in estimating the FFMC code and FWI index. The tolerable errors in FFMC and FWI can be estimated from Figs. 5, 6 and Tables II, III, based on the application requirements. After computing k, we need to activate a subset of sensors to ensure k-coverage, and keep other sensors in sleep mode to conserve energy. In Sec. 4.2, we present a distributed protocol to achieve this.

4.2 Distributed K-Coverage Algorithm

To achieve k-coverage ($k \geq 1$) in different clusters of the monitored forest, we need a distributed, energy-efficient, algorithm. As mentioned above, area coverage can be approximated by ensuring that all node locations are covered. Thus, the k-coverage problem becomes selecting a minimum subset of nodes to cover all nodes. Selecting the minimum subset for activation is desired because it reduces total energy consumption and thus prolongs the network lifetime. Computing the minimum subset, however, is NP-hard [Yang et al. 2006]. In [Hefeeda and Bagheri 2007], we designed a logarithmic factor approximation algorithm to solve the k-coverage problem. Our previous work focused on the theoretical analysis of the algorithm without paying much attention to the specific application. In the current work, we customize this algorithm to the forest fire detection application, and we consider several issues that were not addressed before. We first summarize the key ideas of our k-coverage algorithm.

We model the k-coverage problem as a set system for which an optimal hitting set corresponds to an optimal solution for coverage. At a high level, our algorithm begins with selecting a set of points referred to as ϵ-net. Initially the number of points in the ϵ-net is 1. All points are assigned weights that are initially equal to 1. A point is added to the ϵ-net with a probability proportional to its weight. If a point q is selected to be in ϵ-net, k nodes inside a disk of radius r_s centered at q are randomly selected to be part of the solution for k-coverage. r_s is the sensing range of a node. The algorithm then verifies if activating the selected set of sensor locations sufficiently covers all points. If so, it terminates. Otherwise, the weight of a point that is not sufficiently covered is doubled and a new ϵ-net with the same size is selected. After a specific number of iterations, if no solution was found, the size of the ϵ-net is doubled to allow a larger solution. It is proved in the extended version of [Hefeeda and Bagheri 2007] that this algorithm terminates and achieves a solution of size within a logarithmic factor of the optimal.

The above algorithm is centralized, but it can easily be implemented in a distributed manner. This is because it only maintains two global variables, ϵ-net size and aggregate weight of all points, and both variables can be estimated with local information. The distributed algorithm, called DRKC, estimates the ϵ-net size as follows. All nodes keep track of the desired ϵ-net size using the local variable $netSize$, which is initially set to 1. Since the ϵ-net size is simply doubled in every iteration, nodes can get an accurate estimate of the desired size of the ϵ-net for the current iteration. Knowing the desired ϵ-net size enables nodes to independently contribute to the current ϵ-net in a way when all contributions are added up, the desired global ϵ-net is produced. A node decides (locally) to be part of the ϵ-net with a probability $p = (weight/totalWeight) \times netSize$. If a node is chosen, it will activate k other nodes to be part of the k-coverage solution by broadcasting an ACTIVATE message. The ACTIVATE message contains a probability P_a which is calculated as $(k - curCoverage)/(neighborSize - curCoverage)$, where k is the requested coverage degree, and $curCoverage$ is the current degree of coverage at the node. When a node receives an ACTIVATE message, it becomes active with probability P_a. P_a is so chosen to make the expected number of newly activated nodes equal to $k - curCoverage$ which is needed by the sender of the ACTIVATE message.

A node uses the variable $totalWeight$ to estimate the aggregate weight of all nodes. $totalWeight$ is initialized to the number of nodes in the network n. In the centralized algorithm, the weight of only one under-covered node is doubled. To emulate this in the distributed algorithm, an under-covered node doubles its weight with probability $1/n_u$, where n_u is the number of under-covered nodes in the network. n_u is approximated locally as $(n - netSize)$. Thus, the expected number of nodes that double their weights is equal to

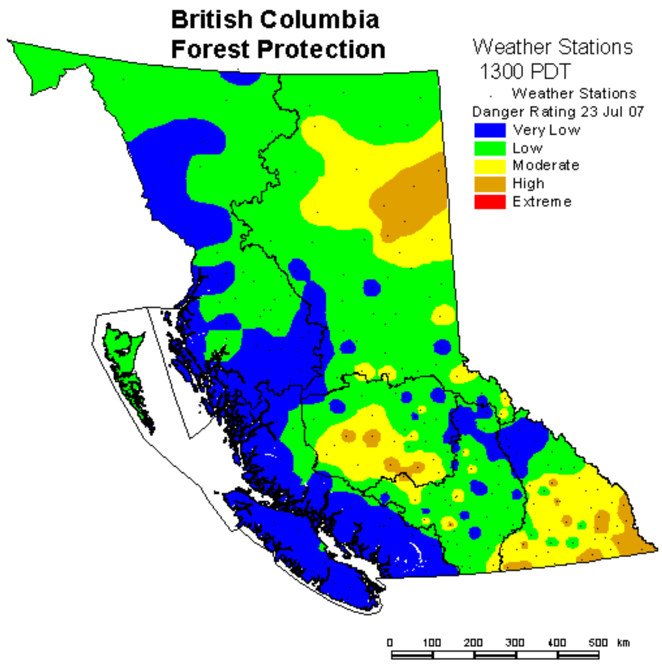


Fig. 8. The need for coverage with different degrees in forest fires. The picture shows different fire danger levels at different zones. Reproduced with permission from the Ministry of Forests and Range, Protection Program, BC, Canada.

1, which is the same as in the centralized case. Now since the total weight is increased by the weight of a single under-covered node in each iteration, a node can estimate the total weight by adding the average weight of nodes $(totalWeight/n)$ to its own current value of $totalWeight$. To verify k-coverage, each node independently checks its own coverage by listening to messages exchanged in its neighborhood, and counting number of active nodes. A node terminates the algorithm if it is sufficiently covered. Otherwise, it doubles its weight with probability $1/n_u$, and starts another iteration. It is shown in the extended version of [Hefeeda and Bagheri 2007] that the distributed algorithm: (i) performs close to the centralized algorithm in terms of number of activated sensors, (ii) converges fast, (iii) does not rely on sensor location information, and (iv) does not require fine-grained clock synchronization.

4.3 Application-Oriented Data Aggregation

We propose a simple data aggregation scheme explicitly designed for forest fire detection applications. Based on our analysis of the FWI System in Sec. 3.3, the application can interpret and uses only the FFMC code and the FWI index. Thus, individual sensor readings of various weather conditions may not be of interest to the application. Therefore, there is not need to deliver all these detailed data to the processing center. We propose that cluster heads aggregate individual sensor readings by computing the FFMC and FWI using their respective closed-form equations [Wagner and Pickett 1985]. Each cluster head periodically collects weather conditions from sensors in its cluster and computes FFMC and FWI.

Cluster heads carry out significant load, because they compute FFMC and FWI from complicated equations and participate in data forwarding across clusters. Hence, unless the role of the cluster head is rotated, heads run out of energy and die earlier than other nodes. This may cause coverage holes in some areas, or it could partition the network and disrupt data forwarding. To balance the load across all nodes, we propose to scale the probability of a node activating itself P_a upon receiving an ACTIVATE message by its level of remaining energy. Thus, a node that has been a cluster head before will have a smaller probability of becoming cluster head again. Our simulation results (Sec. 5) show that this simple extension balances the load across all nodes and significantly prolongs the network lifetime.

4.4 Unequal Monitoring of Forest Zones

Unequal monitoring of different forest zones is important in forest fire detection systems, because some areas may have higher fire potential than others. For example, dry areas at higher elevations are more susceptible to fires than lower and more humid areas. Moreover, it is usually important to monitor parts of the forest near residential and industrial zones with higher reliability and accuracy. To confirm the above intuition, we collected real data on the fire danger rating produced by the Protection Program of the Ministry of Forests and Range, in the Province of British Columbia, Canada. Sample of the data is shown in Fig. 8 for 23 July 2007. The figure shows several hot spots with 'High' danger rating within larger areas with 'Moderate' rating. The number, size, and locations of the hot spots are dynamic, because they depend on weather conditions. Maps such as the one shown in Fig. 8 are produced daily.

To support unequal monitoring of forest zones, we propose to cover the forest with different degrees of coverage at different zones. Intuitively, in hot spots, the FFMC and FWI are expected to be in the high ranges of their scales, and small errors in these ranges could lead to mis-classifying a fire and/or taking the wrong re-actions. For example, the 'Very High' range of FFMC in Table II is 89–91 (only two units), while the 'Low' range is 0–76. As discussed in Sec. 4.1, higher accuracy in computing FFMC and FWI require collecting weather conditions more accurately, which can be achieved by controlling the coverage degree k.

We extend our distributed k-coverage algorithm (DRKC), described in Sec. 4.2, to support coverage with various degrees at different zones in the forest at the same time. We are not aware of any other coverage protocol in the literature that supports this feature. We first model areas requiring different coverage degrees as polygons, an example is shown in Fig. 9. Then, the vertices of each polygon are communicated to all cluster heads in the network. Each cluster head in turn can determine whether they are within the area with the different coverage. If this is the case, it notifies the sensors in its own cluster to adjust their operation to achieve the new requested coverage degree. This is easily done by our DRKC algorithm, because coverage verification in DRKC is done by individual nodes: each node decides locally to terminate the algorithm if it finds itself sufficiently covered by its active neighbors. Otherwise, it doubles its weights with a small probability and begins a new iteration to activate more of its neighbors. In the evaluation section, we verify that coverage with various degrees can indeed be achieved by DRKC.

As discussed in Sec. 4.2, our DRKC does not use any location information. Thus, it

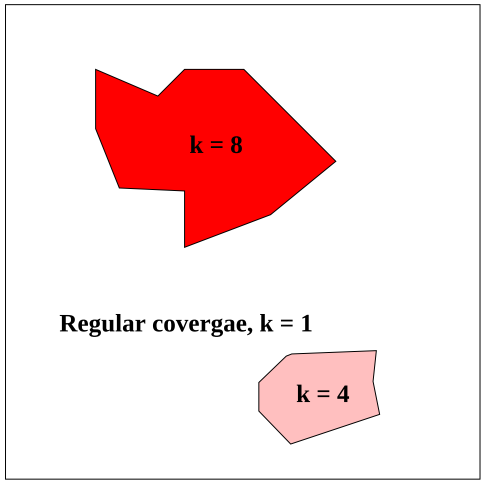


Fig. 9. Modeling forest zones that require different degrees of coverage as polygons.

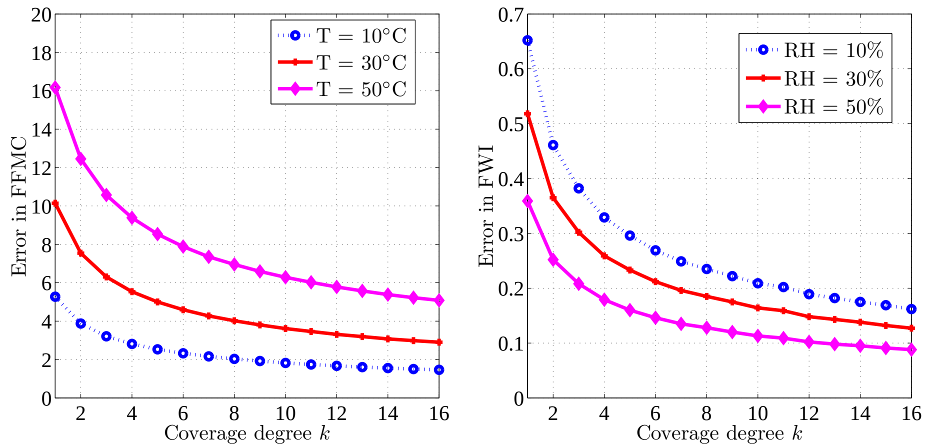
saves the overhead of localization protocols, or the cost of equipping sensors with GPS, which is a significant saving considering the scale of the forest fire detection system. However, cluster heads need to determine whether or not they are inside some hot spots. This can be achieved by associating sensor IDs to their approximate locations during the deployment process. For example, during deployment, sensors with specific ID ranges can be thrown by the aircraft in target geographical locations. This mapping is maintained by the data processing center to dynamically configure the sensor network. It is important to emphasize that the approximate locations do not impact the operation of our DRKC protocol, they are only used to delineate hot spots. Hot spots are usually measured in kilometers, and thus approximate locations are suitable for specifying them.

5. EVALUATION

In this section, we evaluate various aspects of the proposed wireless sensor network for forest fire detection. We start by assessing the accuracy in estimating the FFMC and FWI fire indexes as a function of the coverage degree k. We also analyze the tradeoff between the error in sensor readings and the required coverage degree. Then, we evaluate our k-coverage algorithm and verifies that it can provide unequal monitoring of the forest zones, and balances the load across all sensors and hence prolongs the network lifetime.

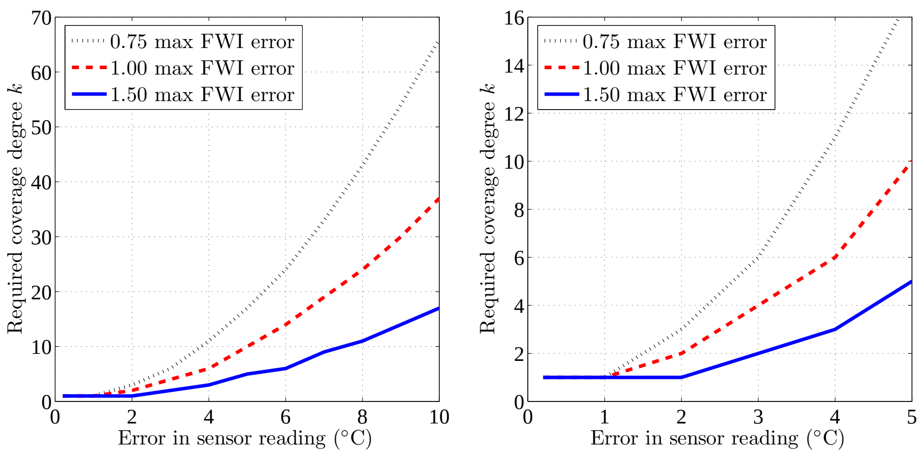
5.1 Accuracy of FFMC and FWI

In Section 4.1, we established a relationship between the coverage degree and the accuracy in estimating FFMC and FWI. We numerically analyze this relationship. We vary the coverage degree k between 1 and 16. We assume that the accuracy of the temperature sensing board is $4°$C, i.e., $\sigma_T = 2$. All calculations are done for a confidence level of 95%. For each value of k, we compute the error in estimating the temperature δ_T. Then, we use the software program that computes the FFMC and FWI indexes [Wagner and Pickett 1985] to determine the maximum error in these indexes, given a $\pm\delta_T$ error in the temperature T. We repeat the experiment for several values of the temperature and humidity. Some of the results are given in Fig. 10. First, as predicted by the analysis in



(a) (b)

Fig. 10. Error in calculating: (a) FFMC Code, (b) FWI Index for various coverage degrees and in different weather conditions.



(a) (b)

Fig. 11. The tradeoff between the accuracy in sensor reading and the required coverage degree, given a maximum tolerable error in the FWI index. (a) considers a wide range for sensor accuracy, while (b) zooms in the small range between 0–5.

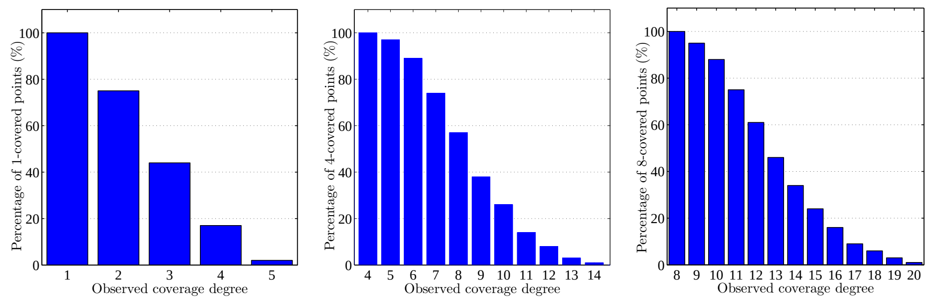
Sec. 4.1, the figure shows that higher coverage degrees result in smaller errors in FFMC and FWI. Second, the figure exposes an important issue: the error in FFMC and FWI is amplified in extreme conditions (high temperatures and low humidity), which is due to the non-linearity of the complex equations that determine FFMC and FWI. For example, Fig. 11(a) indicates that an error up to 2 units in FFMC could result when $k = 2$ and the temperature is $10°$C, while this error could be as high as 12 units if the temperature is $50°$C with the same k value. This means that in extreme conditions, which are the most important for the forest fire detection system, even small errors in sensing the temperatures could lead to significant errors in FFMC and FWI, which may lead the sensor network operators to take incorrect actions. This also highlights the importance of unequal monitoring of forest zones: host spots of the forest need to be covered with higher degrees to provide accurate assessment of the potential and intensity of fires. Furthermore, the results in Fig. 10 can be used to *dynamically* configure the sensor network such that higher coverage degrees are enforced as the weather conditions get more severe. Dynamic configuration of the sensor network (or parts of it) is easily achieved by our k-coverage algorithm because of its distributed nature, this is demonstrated in the next subsection.

In the previous experiment, the error in sensor reading is fixed. In our next experiment, we analyze the tradeoff between the accuracy of the sensing boards and the required coverage degree such that a given maximum error in FFMC and FWI is not exceeded. Since forest fire detection is an important application for sensor networks, sensor manufacturers may customize or even create new products explicitly for this application. In this case, understanding the needed accuracy of the sensing module could result in significant savings especially for mass production of sensors.

We consider a wide range of accuracy for sensing boards; the results presented here are for temperature sensors, but the analysis can be carried out for other weather conditions as well. As mentioned in Sec. 4.1, the error in sensor reading is specified as $2\sigma_T$. We vary the error in sensor reading from $0.25°$C to $10°$C, which captures the the range of accuracy achieved by very accurate and expensive sensors to rough and cheap sensors. For each value of the error reading, we compute the required coverage degree k to meet the given error in FWI and FFMC using their equations. We repeat for a few target errors in FWI and FFMC. We plot the results for the FWI index in Fig. 11; Fig. 11(a) shows the results for the full error range, while Fig. 11(b) zooms in the small error range between 0–5 for illustration. The figure clearly exposes the tradeoff: for larger errors in sensor readings (i.e., cheaper sensors), higher coverage degrees are required to meet the target error in FWI and FFMC. For example, for a maximum error in FWI of 1.0 unit, a coverage degree of 1 is needed when sensors that have temperature error readings up to $1°$C are deployed, whereas a coverage degree of 8 would tolerate temperature error readings up to $4.5°$C while achieving the same accuracy in FWI. Higher coverage degrees require keeping more sensors active, which means that they will be depleted from energy faster. Therefore, to achieve a target network lifetime, more sensors will need to be deployed for higher coverage degrees. However, with mass production of less-accurate sensors, increasing the degree of coverage could result in more cost-effective sensor networks that achieve the same function.

5.2 Evaluation of the k-coverage Algorithm

We have implemented a packet-level simulator for our distributed k-coverage algorithm in C++. Simulators like NS-2 did not scale to the number of nodes (in order of thousands) needed to evaluate our algorithm. We fix an area of size $1km \times 1km$ and vary the coverage degree k between 1 and 8. We deploy up to 12,000 sensors uniformly at random with the same density over the entire area. The large number of sensors is needed to support coverage with high degrees. We assume that the sensing range of nodes is $100m$; using other sensing ranges does not impact the operation of our algorithm, because it only changes the fraction of active sensors. We employ the energy model in [Ye et al. 2003] and [Zhang and



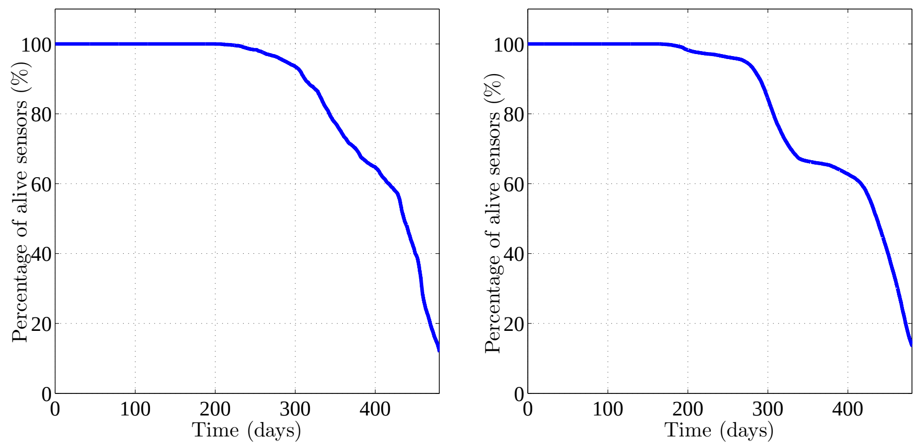
(a) Requested $k = 1$ (b) Requested $k = 4$ (c) Requested $k = 8$

Fig. 12. Coverage with different degrees achieved by our algorithm.

Hou 2005], which is based on the Berkeley Mote hardware specifications. In this model, the node power consumption in transmission, reception, idle and sleep modes are 60, 12, 12, and 0.03 mW, respectively. The results are summarized in the following.

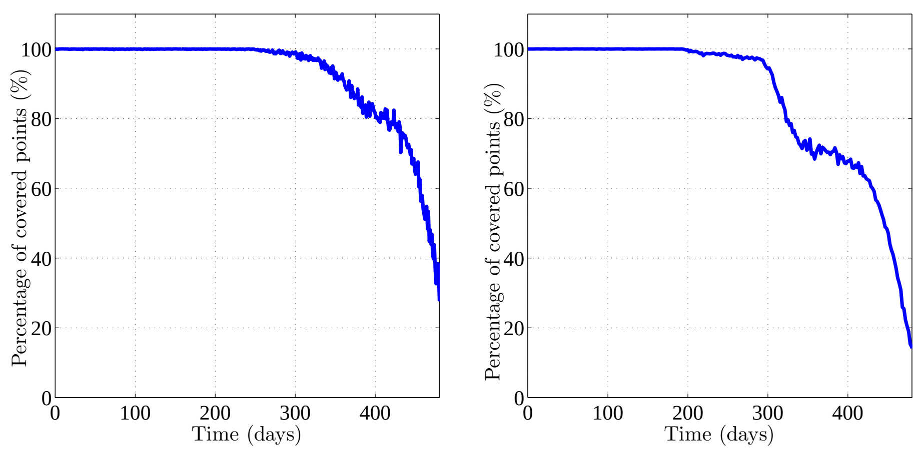
Unequal Monitoring using Different Coverage Degrees. In this experiment, we validate that our distributed k-coverage algorithm can maintain coverage with various degrees to achieve unequal monitoring of different zones in the forest. We assume there are two hot spots inside the forest that need higher coverage degrees than other areas, as shown in Fig. 9. The two spots are modeled as two polygons. The requested coverage degree in one spot is 8 and in the other is 4. Nodes outside the hot spots are requested to have a coverage degree of 1. We run our algorithm and notify nodes inside the hot spots of the different coverage degrees. We let the algorithm converge, and we check the coverage degree of every single point in the area. We plot the achieved coverage distribution in each area in Fig. 12. The results indicate that in each of the hot spots, our algorithm indeed achieves the requested coverage degree while it provides 1-coverage in the rest of the area. Fig. 12 also shows that our algorithm does not over cover areas, because the fraction of nodes having higher-than-requested coverage degrees decreases fast. This is important to save energy and prolong network lifetime.

Load Balancing. We study the average load on individual nodes and on the network lifetime under our k-coverage algorithm. We measure the load on a node by the energy consumed by that node. Once a node runs out of energy, it is assumed to be failed or dead. We run our algorithm till all nodes are dead. After each round of the algorithm, we count the number of alive nodes. We plot the percentage of alive nodes versus time. We repeat the whole experiment for various coverage degrees, from $k = 1$ to 8. Sample of the results are shown in Fig. 13. As the figure shows, most of the nodes stay alive for a long period (more than 200 days). Then, they gradually die. This means that the algorithm did not over utilize some nodes in early rounds, otherwise, they would have died earlier. Notice that the energy of a node is enough for it to be active in a few days, and if a node were chosen as a cluster head for several times, it will probably survive for only a few hours. These results confirm that our algorithm distributes the load uniformly across all deployed nodes. This is critical in order to keep nodes alive for the longest possible period and achieve more reliable coverage. This also extends the network lifetime as shown by our next experiment.



(a) $k = 1$ (b) $k = 8$

Fig. 13. Our k-coverage algorithm balances load across all nodes, since most of them stay alive for long periods.



(a) $k = 1$ (b) $k = 8$

Fig. 14. Our k-coverage algorithm prolongs network life, because 100% of the area is k-covered is over long periods.

Network Lifetime and Node Failures. Next, we analyze the sensor network lifetime under our k-coverage algorithm as sensors dynamically fail when they run out of energy. We define the network lifetime as the time till the coverage drops below 100%, i.e., there are some points in the area that have coverage less than k. Analyzing the network lifetime is critical in a forest fire detection system, because the sensor network should last for at least one fire season. We use the same setup as in the previous experiment, except we measure coverage not the number of alive nodes. We run the simulation for a long time and periodically check the coverage degree for every single point in the area. A point is considered covered if its coverage degree is at least k. We vary k between 1 and 8 and plot some of the results in Fig. 14. The figure shows that 100% coverage of the area is maintained through a long period of time, more than 200 days. This is because our algorithm uniformly distributes load on nodes.

Fig. 14 also shows that coverage decreases at a slower rate than the number of alive nodes in Fig. 13. For example, in Fig. 13(a), the number of alive nodes starts to drop below 100% around day 200, while 100% coverage is maintained till almost day 300 as shown in Fig. 14(a). This demonstrates the robustness of our algorithm against node failures. In addition, the results in Fig. 14 imply that alive nodes are not grouped in certain subareas, rather, they are uniformly distributed in the whole area. Therefore, our k-coverage algorithm prolongs the network lifetime because it uniformly balances the load across all nodes and it keeps alive nodes distributed throughout the whole area.

6. CONCLUSIONS

We presented the design of a wireless sensor network for early detection of forest fires. Our design is based on the Fire Weather Index (FWI) System, which is backed by decades of forestry research. The FWI System is comprised of six components: three fuel codes and three fire indexes. The three fuel codes represent the moisture content of the organic soil layers of forest floor, whereas the three fire indexes describe the behavior of fire. By analyzing data collected from forestry research, we showed how the FWI System can be used to meet the two goals of a wireless sensor network designed for forest fires: (i) provide early warning of a potential forest fire, and (ii) estimate the scale and intensity of the fire if it materializes. To achieve these goals, we designed our sensor network based on two main components of the FWI System: the Fine Fuel Moisture Code (FFMC), and the Fire Weather Index (FWI). The FFMC code is used to achieve the first goal and the FWI index is used to achieve the second.

We modeled the forest fire detection problem as a k-coverage problem, with $k \geq 1$. We computed the required coverage degrees to achieve a given accuracy level in estimating different components of the FWI System. We then described the application of our distributed k-coverage algorithm to solve the k-coverage problem. Our algorithm is simple to implement and does not require any specific node deployment schemes. Therefore, nodes can be uniformly deployed by, for example, throwing them from an aircraft. This significantly facilitates node deployment in real life. We showed through simulations that our algorithm: (i) balances load across all deployed nodes, and therefore maintains reliable coverage and significantly prolongs the network lifetime; and (ii) can provide various coverage degrees at different areas of the forest, and thus can achieve higher detection accuracy in important areas such as near residential or industrial neighborhoods.

Acknowledgment

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