Coal Burn Detection using Wireless Sensor Network with Evidence Combination

M.Syed Mohamed, M.Mohamed Sathik, K.Senthamarai Kannan

Abstract – It is a well known fact that the coal required for the operation of the Thermal Power Plants is stored in a Coal Yard. But, the difficulty of using the Coal yard is the nature of the self burning of the coal. At atmospheric temperature, the coal burns itself and becomes ash reducing the quality of the coal. A lot of de–ashing methods are available such as pouring water which further reduces the quality of coal. The present method of de-ashing by adding water in large quantity leads to decrease the quality of coal. Hence, it is necessary to detect and predict fire in Coal yard more promptly and accurately to minimize the quality of coal. This paper introduces an efficient and intelligent smart system for coal fire detection using wireless sensor network with evidence combination.

Index Terms — Coal burn, SVM, Dempster Shafer , Classifer, Wireless Sensor Network.

I. INTRODUCTION

Coal-fire in coalfield is either because of fire infection from adjacent fire-affected coal seams or spontaneous combustion of coal. Oxidation of coal is an exothermic process and if the heat generated is allowed to accumulate, then the accumulated temperature ignites the coal. This natural process is called spontaneous combustion and is one of the major causes of coal fire in coalfield. Thus India is losing good quality coal prior to its exploitation. Hence, there is a need for detection and monitoring of coal fires in coalfields in order to control them effectively.

Self-ignited, naturally occurring coal fires and fires resulting from human activities persist for decades in underground coal mines, coal waste piles, coal yards and unmined coal beds. These uncontrolled coal fires occur in all coal-bearing parts of the world and pose multiple threats to the global environment because they emit greenhouse gases—carbon dioxide (CO2), and methane (CH4)—as well as mercury (Hg), carbon monoxide (CO), and other toxic substances. The contribution of coal fires to the global pool of atmospheric CO2 is little known but potentially significant. For China, the world's largest coal producer, it is estimated that anywhere between 10 million and 200 million metric tons (Mt) of coal reserves (about 0.5 to 10 percent of production) is consumed annually by coal fires or made inaccessible owing to fires that hinder mining operations (Rosema and others, 1999; Voigt and others, 2004). At this proportion of production, coal amounts lost to coal fires worldwide would be two to three times that for China.

A. Self-Heating Processes Leading to Spontaneous Combustion

Exposure of underground coal and (or) coal waste piles to atmospheric oxygen promotes spontaneous heat-generating reactions, primarily oxidation of the coal itself, and the oxidation of pyrite present in coal. In this process, carbon, the largest constituent of coal, combines with available oxygen to produce CO_2 and heat. Similarly, the sulfur present in pyrite combines with oxygen to produce sulfate, releasing heat, and, in the presence of water, forming sulfuric acid that can result in acidic drainage. Absorption of water vapor onto coal surfaces and interaction of bacteria with coal are other heat-producing processes (Kim, 2007). Where oxygen is present and because of the decrease in the minimum required temperatures for coal combustion at depth and the insulating capacity of coal overburden, these heat-producing reactions can result in spontaneous combustion or extend the life of coal fires started by inadvertent combustion in mines. Where exposed at the surface, as in the Powder River Basin of Wyoming and Montana, coal beds can be ignited by wildfires, lightning, and human activities, as well as by spontaneous combustion (Heffern and Coates, 2004).

B. Impact of Emissions

Direct hazards to humans and the environment posed by coal fires include emission of pollutants, such as CO, CO_2, nitrogen oxides, particulate matter, sulfur dioxide, toxic organic compounds, and potentially toxic trace elements, such as arsenic, Hg, and selenium (Finkelman, 2004). Mineral condensates formed from gaseous emissions around vents pose a potential indirect hazard by leaching metals from mineral-encrusted surfaces into nearby water bodies. Coal is outright dangerous, for various reasons, such as:

- Burning coal emits harmful waste such as carbon dioxide, sulphur dioxide, nitrogen oxides, sulphuric acids, arsenic and ash
- It causes heavy pollution.
- The burning of coal in large quantities, such as in factories can lead to acid rains.
- Coal mining is harmful to the landscape and the large and noisy equipment used for mining may affect local wildlife.
- It is not very well known but releases from coal combustion contain naturally occurring radioactive materials–mainly uranium and thorium**.** To give a comparison, coal fired power plants produce 100 to 400 times as much radioactive material as nuclear power plants are permitted to.

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II. WIRELESS SENSOR NETWORK

Recent advances in micro-electro-mechanical systems technology, wireless communications, and digital electronics have enabled the development of low-cost, low-power, multifunctional sensor nodes that are small in size and communicate in short distances. These tiny sensor nodes, which consist of sensing, data processing, and communicating components, leverage the idea of sensor networks based on collaborative effort of a large number of nodes.

Sensor networks represent a significant improvement over traditional sensors, which are deployed in the following two ways:

Sensors can be positioned far from the actual phenomenon, i.e., something known by sense perception. In this approach, large sensors that use some complex techniques to distinguish the targets from environmental noise are required.

Several sensors that perform only sensing can be deployed. The positions of the sensors and communications topology are carefully engineered. They transmit time series of the sensed phenomenon to the central nodes where computations are performed and data are fused. A sensor network is composed of a large number of sensor nodes, which are densely deployed either inside the phenomenon or very close to it. The architecture of the wireless sensor network is as shown in the Figure-1 below.

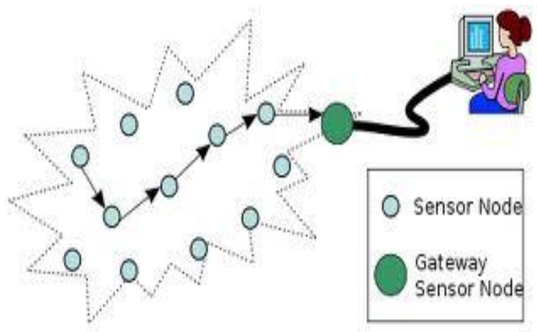

Figure 1: The architecture of wireless sensor network.

The position of sensor nodes need not be engineered or pre-determined. This allows random deployment in inaccessible areas of coal field. On the other hand, this also means that sensor network protocols and algorithms must possess self-organizing capabilities. Another unique feature of sensor networks is the cooperative effort of sensor nodes. Sensor nodes are fitted with an on-board processor. Instead of sending the raw data to the nodes responsible for the fusion, sensor nodes use their processing abilities to locally carry out simple computations and transmit only the required and partially processed data.

The above described features ensure a wide range of applications for sensor networks. Some of the application areas are health, military, and security. Sensor networks can also be used to detect foreign chemical agents in the coal, air and the water. They can help to identify the type, concentration, and location of pollutants. In essence, sensor networks will provide the end user with intelligence and a better understanding of the coal field. It seems that, in future, wireless sensor networks will be an integral part of our lives, more so than the present-day personal computers.

III. DESCRIPTION OF CLASSIFIERS

A. Support Vector Machine:

The main aim of Support Vector Machines (SVMs) is to find hyper-planes that separate data points in to their respective classes. The better the separation achieved the better the data classification that is ultimately possible. Support Vector Machine (SVM) has been recognized as a better tool to deal with high-dimensionality problems like in the case of coal as it involves thousands of acres. In order to determine the equation of the hyper-plane, the support vector machine searches for those data points that lie closer to data points of another class. These points are called "support vectors". The number of input vectors defines the dimension of the input space. The simplest case has two input variables and thus its input space is two dimensional. If there are two linearly separable classes of data, the goal is to find a line that separates the two classes from each other, thereby establishing the input values that define the two classes. Therefore, the optional hyper-plane is defined as

$$X + b_0 = 0. \quad (1)$$

B. SUPPORT VECTOR MACHINE ^{LIGHT}

SVM^{light} is nothing but an implementation of Support Vector Machines (SVMs) in C and it is a popular method of classification. The main features of the program include: fast Optimization algorithm considering the "Shrinking" , Caching of Kernel evaluations, use of folding in the linear case. The advantage of using SVM^{light} is its ability to handle many thousands of support vectors and several hundred-thousands of training samples. SVM^{light} uses sparse vector representation. SVM^{light} supports standard kernel functions and lets you define your own. The polynomial kernel used in SVM^{light} is defined as k(x, y) = K(x′ y). SVM^{light} computes XiAlpha-estimates of the error rate, the precision, and the recall. SVM^{light} efficiently computes Leave-One-Out estimates of the error rate, the precision, and the recall. SVM^{light} includes algorithm for approximately training large transductive SVMs (TSVMs).

C. Support Vector machine Polynomial (SVM^{Poly})

We can also directly fit a second-order polynomial function, $a+cx+qx^2$, to the data points generated from the exponential function *ex*, and determine the coefficients *a, c, q* in a least squares sense. For a certain value that γ takes, a polynomial function is determined so as to best fit the data points uniformly generated by *ex* within the range [0, 2γ]. As a result, we have a set of polynomial functions each corresponding to one of different values that γ could take. The preceding uniform polynomial fitting may be strengthened by taking advantage of the empirical distribution of real-world problems.

IV. DEMPSTER-SHAFER THEORY

Dempster-Shafer Theory (DST) is a mathematical theory of evidence. In DST, evidence can be associated with multiple possible events, e.g., sets of events. As a result, evidence in DST can be meaningful at a higher level of abstraction without having to resort to assumptions about the events within the evidential set.

One of the most important features of Dempster-Shafer theory is that the model is designed to cope with varying levels of precision regarding the information and no further assumptions are needed to represent the information. It also allows for the direct representation of uncertainty of system responses where an imprecise input can be characterized by a set or an interval and the resulting output is a set or an interval. There are three important functions in Dempster-Shafer theory: the *basic probability assignment* function (bpa or *m*), the *Belief* function (*Bel*), and the *Plausibility* function (*Pl*).The basic belief assignment (BBA) is a primitive of evidence theory. Generally speaking, the term "basic belief assignment" does not refer to probability in a classical way. The BBA, represented by m(.), defines a mapping of the power set to the interval between 0 and 1, where the BBA of the empty set is 0 and the summation of the BBAs of all the subsets of the power set is 1. The value of the BBA for a given set A (represented as m(A)), expresses the amount of all related and available evidence that supports the claim that a particular element of X (the universal set) belongs to the set A but to no particular subset of A. The value of m(A) is related only to the set A and makes no additional assumptions about any subsets of A. Any further evidence on the subsets of A would be represented by another BBA. The BBA can be shown by the equations:

$$m(X) \rightarrow [0,1] \quad (2)$$

$$m(\varnothing)=0 \quad (3)$$

$$\sum_{\forall A \in X} m(A)=1 \quad (4)$$

For any classification problem, discrete number of classes are defined.. The power set contains all possible subsets. It is possible to see the for probability gives information about support of hypothesis and simultaneously gives information about the negation (compliment). However, in D-S theory, the uncertainty or not knowing is also modeled.

For data fusion, multiple sources of information is combined to give us better judgment of situation. The purpose of accumulation of information is to summarize and simplify a collection of data whether the data is coming from a single source or multiple sources. Combination rules are the special types of accumulation methods for data obtained from multiple sources. These multiple sources provide different measures about the same frame of discernment and Dempster-Shafer theory is based on the assumption that these sources are independent. Dempster introduced his combination rule for two sources:

$$m^{1,2}(C) = \frac{\sum_{A \cap B = C} m^1(A)\, m^2(B)}{\sum_{A \cap B \neq \varnothing} m^1(A)\, m^2(B)} = \frac{\sum_{A \cap B = C} m^1(A)\, m^2(B)}{1 - \sum_{A \cap B = \varnothing} m^1(A)\, m^2(B)} \quad (5)$$

V. PROBLEM STATEMENT AND PROPOSED WORK

The coal fire attributes such as Temperature, Humidity measured periodically by the sensor nodes are sent to the smart systems. The smart system which comprises of three different classifiers described below as 1, 2 and 3 process the data. Each of the classifiers provides beliefs for each class such as burnt and un-burnt. These pieces of evidence are then combined to reach a final decision using Dempster's belief combination formula (Liu Rujie and Yuan Baozong, 2000). In this wireless sensor network, the temperature and humidity of coal in the coal field are considered. Very high temperature and low humidity were the key factors for coal fire. The smart system which comprises of three different classifiers such as Support Vector Machine, SVM^{Light}, SVM^{Poly} denoted as 1, 2 and 3 in the Figure-2 process the data. Each of the above said classifiers provide beliefs for each class such as burnt and un- burnt. These pieces of evidence are then combined to reach a final decision using Dempster Shafer's belief combination formula. Experiments are accomplished on coal data such as Temperature and Humidity. The architecture of the smart system is shown below.

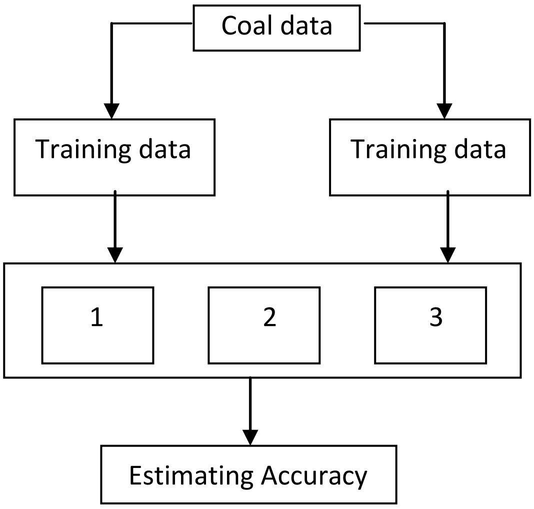

Figure-2 Architecture of Smart System

The approach proposed above has two primary advantages. One advantage is that Robustness across multiple datasets with multiple classifiers and the second one is management of uncertainty in the presence of unequal error costs. Very high temperature and low humidity were the key factors for coal fire.

VI. EXPERIMENTAL RESULTS

The data sets which were used in this analysis were detailed below. Test results were carried out on coal fire data containing temperature and humidity collected by sensor nodes. According to the results taken the accuracy calculation of four test cases are given in the Table-1.

The Table-1 shows the test results of forest data in the form of confusion matrix for four classifiers namely, Support Vector Machine denoted by SVM, SVM^{Light}, SVM^{Poly} and a combination. The combination accuracy is high compared to individual classifier.

Table-1 Accuracy of classifiers for test cases on coal data

Test Numbers	SVM %	SVM^{Light} %	SVM^{Poly} %	Dempster %
Test1	68	64	63	70
Test2	63	67	62	71
Test3	68	68	63	74
Test4	76	70	71	79

VII. CONCLUSION

A novel method is designed for classifying coal fire data by combining multiple classifiers and fusion of evidences using Dempster Shafer Theory. The combination approach shall definitely yield better classification accuracy. The combination approach is robust and reliable. The future work includes that this combination approach may be compared with other rules such as Yager and Inagaki's unified combination rule for better accuracy. Also, other classifiers are considered for handling large data sets and for better performance.

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