International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 6 (2018) pp. 4326-4332

Forest Fire Detection using Proportional Conflict Redistribution Rule2

P. Sudha[1], A. Murugan[2]

[1]*Research Scholar, Dept. of Comp. Sc. and Engineering, Manonmaniam Sundaranar University, Tirunelveli, India.*
[2]*Associate Professor & Head, PG & Research Dept. of Comp. Sc., Dr Ambedkar Government Arts College, Vyasarpadi, Chennai, India.*

Abstract

The objective of this paper is to detect fire in the forest where some plants and trees are prone to fire very easily. The detection of forest fire preserves economic and environmental wealth of forest and defends human life. Wireless Sensor Networks (WSNs) are used to monitor tactical and hazardous sites inside the forest. Failure detection of sensor nodes in this specified application is a major concern. Furthermore, in WSN systems failures are unavoidable due to hardware constraints, unattended distribution areas in the forest and limited resources. This paper introduces Proportional Conflict Redistribution Rule2 (PCR2) rule, which deals better for vague, ambiguous and potentially highly contradictory sources of information due to the failure of nodes and links. For the data of high inconsistent sources of information due to misclassification or network/node failure, the PCR1 rules provides a reliable result. However, for the same high conflicting data, the new combination rule PCR2 provides both dependable and judicious results. The experimental analysis shows that the accuracy of PCR2, while using the incident data received from the failure links and nodes, is more reasonable than that of PCR1 in the framework of forest fire detection and is more consistent and vigorous in combining highly conflicting sources.

Keywords*:* Uncertainty, Belief entropy, Proportional Conflict Redistribution Rule1, Proportional Conflict Redistribution Rule2

INTRODUCTION

Nowadays, the utmost threat in forests is fire and forest fire can be a great peril to the people who live in forests as well as wild life. It is an unrestrained fire happening in nature, which obliterates a forested area [1]. As forest fire has spread over a large area, making its control and stoppage is very tough and even incredible and dreadful at times. Early detection of forest fires is the only way to curtail the damages and casualties apart from defensive measures, using the wireless sensor network systems.

Wireless sensor networks comprise of numerous sensors nodes, which can be used to collect the data in the forest. These captured events from the nodes are sent to the cluster heads. All the cluster heads are connected to a sink, which in turn are connected to a manager node [2]. The collected data are classified using the classifiers with the help of attributes and the conflicting data are distributed to the relevant classes using the combination rule, Proportional Conflict Redistribution (PCR) rule and a decision is taken on the forest fire data regarding fire or no fire.

There are numerous interconnected hardware elements in the network that even if one critical component flops it could cause an outage. It could be a complete or partial failure of any number of devices, such as a router, gateway or network controller [3]. During fire detection evolution in the forest using wireless sensor network there are prospects of node and link failure in the network. Using Proportional Conflict Redistribution rule a combination of data has been achieved to improve the accuracy of detection of fire in the forest.

Section II springs a gesture on wireless sensor network. Section III bounces an awareness on some of the other forest fire detection algorithm and its inadequacies. Section IV articulates about the failure of node or link that occurs in the forest while detecting the fire. Section IV expresses an idea about Proportional Conflict Redistribution (PCR) rule and also explicates the concept of PCR1 and PCR2. An algorithm for PCR2 is designed and an experimental study of PCR1 and PCR2 is engendered once there is a link or node failure in the network while detecting the fire in the forest. Section V elasticities the conclusion during the failure or no failure of link or node, while using PCR1 and PCR2 combination rule.

WIRELESS SENSOR NETWORK

With the recent advancement in the area of wireless sensor networks, electronic components used in the networking have become dramatically inexpensive. This has empowered the development of low-cost and multifunctional sensors that are smaller in size and interconnect very effectively and can be deployed anywhere in the forest easily [4].

Wireless sensor network encompasses several tiny sensor nodes that have more computation power. The tiny sensor nodes of low cost and low battery power sensor devices are deployed in the forest. A sensing unit which is the core component of wireless sensor network is used to capture events of consideration and another significant component called wireless transceiver is used to transform the captured events back to the base station which is called as sink node [5]. Sensor nodes collaborate with one another nodes to accomplish tasks of data classifying, data communication, and data processing.

In the wireless sensor network, sensor nodes collected the Incident data and the poised data are delivered to the sink for the productive monitoring of forest. The consistency of individual link performance and the communication in the network are very crucial in forest fire detection to elude any unexploited detection [6]. The utmost notable advantage of sensor networks is its augmented computation ability to physical atmosphere and it can be deployed in the area where human beings cannot reach in deep forest.

Sensor networks can work for prolonged periods in areas of forest that are unsuited, exciting or ecologically too subtle for human scrutiny. Moreover, the wireless sensor network has the credible to send prosperity of data in which they are systematized and send their connotations across the network to the users, while monitoring the forest [7]. A system of sensor devices is used to realize vast atmospheres of the forest, since a single sensor airs only limited information. The transfer of data can be made using communication component in sensor nodes in the forest. In this paper, sensor nodes can be used to sense temperature and humidity only.

The small sensor nodes, which demands of sensing, data processing, and communicating components, effect the idea of sensor networks based on collaborative effort of a huge number of nodes. A sensor network is self-possessed of large number of sensor nodes, which are densely organized in the forest [8]. The position of sensor nodes need not be plotted or pre-determined. This consensus permits random deployment of sensors in inaccessible areas inside the forest. The captured events of temperature and humidity are sent to the cluster heads, which comprises of group of sensor nodes. All cluster heads are interconnected to a sink and then to a Manager node. The submissive data collected from the forest contains three classes namely Fire, Intermediate Fire and No Fire and four attributes namely Low Humidity, High Humidity, Low Temperature, High Temperature for the purpose of classification. The three classifiers namely, Support Vector Machine denoted by SVM, SVM Radial Basis Function (SVMRBF) (Sigma=0.3) and SVM Radial Basis Function (SVMRBF) (Sigma=0.9999) are used to combine using the fusion rules, namely, PCR1 and PCR2. The results are analysed in the background of link/node failure in the forest. The architecture of a sensor network for forest fire detection is shown in the figure 1.

LITERATURE SURVEY

Abidha, Paul offered a system with Bayes theorem to detect the fire. A Naïve Bayes classifier uses Bayesian statistics and Bayes' theorem to find the probability of each occurrence belonging to an explicit class and is called Naïve because of accentuating on independency of the conventions. Naïve Bayes classifier algorithm uses conditional independence properties, means it assumes that an attribute value on a given class is independent of the values of other attributes [9]. Suppose if an attribute value on a given class is dependent of other attributes then naive Bayes classifier yields inappropriate results. Suppose $X= \{x_1, x_2... x_n\}$ be a set of n attributes, then in Bayesian, X is considered as evidence and H is some hypothesis means, the data of X belongs to specific class C. It is necessary to determine P (H|X), the probability that the hypothesis H holds given evidence i.e. data sample X. According to Bayes theorem the P (H|X) is articulated as

$$P(H|X) = P(X|H)\,P(H) / P(X).$$

Rachna Raghuwanshi narrated a fire detection method using k-nearest neighbour's algorithm (K-NN) and it is a technique for unifying objects based on closest training data in the feature space [10]. KNN is a kind of instance-based learning and the k-nearest neighbour algorithm is amongst the modest of all machine learning algorithms. But the accuracy of the k-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the feature scales are not consistent with their importance.

The authors in Chen, Lam, and Fan [11] offered a method for fire detection and rescue system using wireless sensor networks, where they have shown that improved forest fire detection performance can be accomplished with the use of wireless sensor networks instead of using satellite-based solutions, while costing much less.

Further, Jayaraman, Zaslavsky, and Delsing, proposed a real time forest detection scheme based on neural network classifiers, where, the distributed processing scheme, with data processing at cluster heads, and imperative data gets linked and collected at the central station for ultimate decision making [12]. Under the real time detection environments, the system is multifaceted to interpret and needs healthier tactics for data processing, communication and collection for final decision making.

FAILURE OF WSN NODES

Wireless sensor nodes interconnect the data collected from the supervised forest arena by way of wireless links. The data such as humidity and temperature, collected from the surrounding zones of the forest is advanced, possibly via many hops, to a sink that can use it in the area or is linked to other networks via a gateway. The sensor node in a sensor network is also equipped with wireless-communication devices organized in the forest. The inter-actor harmonization is obligatory in this forest fire detection to provide the finest performance. Due to certain climatic change and noise interruption in the forest, there are several failures in wireless sensor network [13]. In network management of large scale wireless sensor network such as forest fire detection, revelation of faulty link plays a crucial role. In this paper, analysis of results with and without network failure are considered. The architecture of wireless sensor network with link or node failure is shown in the figure 2.

The main causes of node failure in the forest fire detection are due to the battery power depletion in a node causing to drive away from the communication range and the ecological factors taking place in the forest. The quality of service of wireless sensor network is decreased because of node or link failure [14]. If there is a fire, the fire detection system senses as no fire, then the cost is too high beyond our thoughts. To improve the performance of the system the transmissions in the forest must be reliable to detect the fire in the forest effectively and efficiently.

It is very tough to localize the faulty links and nodes in the forest, as the link quality will be suggestively impacted by the natural environment like trees in the forest. In the sensor network, the sensor nodes regularly modify its parent node to forward packets [15]. Undesirably, many recent research works aim to sense the faulty links which had been performing badly but fail to offer an analysis. In this paper a combination rule, PCR2 analyses the high conflict data from the source of information emerged due to link/node failure in the forest to improve the performance of the forest fire detection system.

PRINCIPLE OF PCR RULES

The Proportional Conflict Redistribution Rule (PCR) is used in dynamic fusion of forest fire detection for both the non-degenerate cases and degenerate cases [16]. The PCR rule is another fusion rule with the conflict of $k_{12} = 1$ in the forest fire detection.

Let's $\Theta = \{\theta_1, \theta_2, \ldots\ldots \theta_n\}$ be the frame of the fusion problem under consideration and two belief assignments [17] m_1, m_2 : $G^{\Theta} \rightarrow [0,1]$ such that

$$\sum_{X\in G^{\Theta}} m_i(X) = 1,\ i = 1,2. \tag{1}$$

In the framework of forest fire detection, if $\Theta = \{\theta_1, \theta_2, \theta_3\}$, then $2^{\Theta} = \{\emptyset, \theta_1, \theta_2, \theta_3, \theta_1\cup\theta_2, \theta_1\cup\theta_3, \theta_2\cup\theta_3, \theta_1\cup\theta_2\cup\theta_3\}$. The Basic Belief Assignment (BBA) m: $2^{\Theta} \rightarrow [0, 1]$ is given as

$$\left\{ \begin{array}{c} \sum_{A\in 2^{\Theta}} m(A) = 1 \\ m(\phi) = 0 \end{array} \right\} \tag{2}$$

For example, if $\Theta = \{ \theta_1, \theta_2, \theta_3 \}$ then $D^{\Theta} = \{\emptyset, \theta_1, \theta_2, \theta_3, \theta_1\cup \theta_2, \theta_1 \cup \theta_3, \theta_2 \cup \theta_3, \theta_1 \cup \theta_2 \cup \theta_3, \theta_1 \cap \theta_2, \theta_1 \cap \theta_3, \theta_2\cap\theta_3, \theta_1\cap\theta_2\cap\theta_3, (\theta_1\cup\theta_2)\cap\theta_3, (\theta_1\cup\theta_3)\cap\theta_2, (\theta_2\cup\theta_3)\cap\theta_1, (\theta_1\cap\theta_2)\cup\theta_3, (\theta_1\cap\theta_3)\cup\theta_2, (\theta_2\cap\theta_3)\cup\theta_1, (\theta_1\cap\theta_2)\cup(\theta_1\cap\theta_3)\cup (\theta_2\cap\theta_3), (\theta_1\cup\theta_2) \cap (\theta_1 \cup \theta_3) \cap (\theta_2 \cup \theta_3)\}$. The Generalized Basic Belief Assignment (GBBA), is defined as the mapping m: $D^{\Theta} \rightarrow [0, 1]$ and given as

$$\left\{ \begin{array}{c} \sum_{A\in D^{\Theta}} m(A) = 1 \\ m(\phi) = 0 \end{array} \right\} \tag{3}$$

The general principle of the Proportional Conflict Redistribution Rules (PCR for short) is:

- apply the conjunctive rule depending on theory, i.e. G^{Θ} can be either 2^{Θ} or D^{Θ},
- calculate the total or partial conflicting masses,
- then redistribute the conflicting mass (total or partial) proportionally on non-empty sets involved in the model according to all integrity constraints.

Proportional Conflict Redistribution Rule1

Proportional Conflict Redistribution Rule1 (PCR1) is the simplest and the easiest version of proportional conflict redistribution for combination. The basic idea for PCR1 is only to compute the total conflicting mass k_{12} and not about the partial conflicting masses [18]. The total conflicting mass is then distributed to all non-empty sets proportionally with respect to their corresponding non-empty column sum of the associated mass matrix. The PCR1 is defined $\forall(X\neq\emptyset)\epsilon G^{\Theta}$ by,

For combination of s = 2 sources

$$m_{PCR1}(X) = [\sum_{\substack{X_1,X_2\in G^{\Theta}\\ X_1\cap X_2 = X}} m_1(X_1)m_2(X_2)] + \frac{C_{12}(X)}{d_{12}}.K_{12} \tag{4}$$

where,

$C_{12}(X)$ is the non-zero sum of the column of X in the mass matrix M = $\begin{bmatrix} m_1 \\ m_2 \end{bmatrix}$

i.e. $c_{12}(X) = m_1(X) + m_2(X) \neq 0$

K_{12} is the total conflicting mass

d_{12} is the sum of all non-zero column sums of all non-empty sets.

Proportional Conflict Redistribution Rule2

In Proportional Conflict Redistribution Rule2 (PCR2), the total conflicting mass k_{12} is distributed only to the non-empty sets involved in the conflict but, not to all non-empty sets and taken the canonical form of the conflict proportionally with respect to their corresponding non-empty column sum [19]. The redistribution is then more exact (accurate) than in PCR1. PCR2 has the ability to deal with all cases or models.

PCR2 formula for two sources s=2 is

$\forall(X\neq\emptyset)\ \epsilon\ G^{\Theta}$

$$m_{PCR2}(X) = [\sum_{\substack{X_1,X_2\in G^{\Theta}\\ X_1\cap X_2 = X}} m_1(X_1)m_2(X_2)] + C(X)\frac{C_{12}(X)}{e_{12}}.K_{12} \tag{5}$$

where

C(X) = 1, if X involved in the conflict or C(X) = 0, otherwise.

$C_{12}(X)$ is the non-zero sum of the column of X in the mass matrix

$$c_{12}(X) = m_1(X) + m_2(X) \neq 0$$

K_{12} is the total conflicting mass

e_{12} is the sum of all non-zero column sums of all non-empty sets only involved in the conflict.

Algorithm for PCR2

1. Organize the mass matrix associated with the beliefs assignments $m_1(.)$ and $m_2(.)$

$$m_1 = [m_1(\theta_1)\ m_1(\theta_2)\ m_1(\theta_1 \cup \theta_2)]$$

$$m_2 = [m_2(\theta_1)\ m_2(\theta_2)\ m_2(\theta_1 \cup \theta_2)]$$

2. The fusion of two sources is

$$M_{12} = \begin{bmatrix} m_1 \\ m_2 \end{bmatrix} = \begin{bmatrix} m_1(\theta_1) & m_1(\theta_2) & m_1(\theta_1\cup\theta_2) \\ m_2(\theta_1) & m_2(\theta_2) & m_2(\theta_1\cup\theta_2) \end{bmatrix},$$

3. Calculate the conjunctive consensus

$$m_{\cap}(.) = [m_1 \oplus m_2](.)$$

$$m_{\cap}(X) = \sum_{\substack{A,B \in D^{\Theta} \\ A \cap B = X}} m_1(A) m_2(B)$$

4. Compute the conjunctive masses $C_{12}(X)$

$$c_{12}(X = \theta_1) = m_1(\theta_1) + m_2(\theta_1)$$

$$c_{12}(X = \theta_2) = m_1(\theta_2) + m_2(\theta_2)$$

$$c_{12}(X = \theta_1 \cup \theta_2) = m_1(\theta_1 \cup \theta_2) + m_2(\theta_1 \cup \theta_2)$$

5. Total conflicting mass K_{12} is evaluated

$k_{12} = 1 - m_{\cap}(X)$

6. Conflicting mass is distributed between $m_{\cap}(X)$ proportionally

$$\frac{w(\theta_1)}{c_{12}(\theta_1)} = \frac{w(\theta_2)}{c_{12}(\theta_2)} = \frac{w(\theta_1 \cup \theta_2)}{c_{12}(\theta_1 \cup \theta_2)} =$$

$$= \frac{w(\theta_1) + w(\theta_2) + w(\theta_1 \cup \theta_2)}{c_{12}(\theta_1) + c_{12}(\theta_2) + c_{12}(\theta_1 \cup \theta_2)}$$

$$= \frac{k_{12}}{e_{12}}$$

because

$$c_{12}(\theta_1) + c_{12}(\theta_2) + c_{12}(\theta_1 \cup \theta_2)$$

$$= \sum_{x_1 \varepsilon D^{\Theta} |\{\phi\}} m_1(X_1) + \sum_{x_2 \varepsilon D^{\Theta} |\{\phi\}} m_2(X_2) = e_{12}$$

7. Relevant conjunctive masses are calculated and multiplied with the related proportional conflicting masses

$$\left\{ \begin{aligned} w(\theta_1) &= c_{12}(\theta_1).\frac{k_{12}}{d_{12}} \\ w(\theta_2) &= c_{12}(\theta_2).\frac{k_{12}}{d_{12}} \\ w(\theta_1 \cup \theta_2) &= c_{12}(\theta_1 \cup \theta_2).\frac{k_{12}}{d_{12}} \end{aligned} \right\}$$

Experimental Analysis of PCR1and PCR2 rule for WSNs

Nearly 151 samples of reflexive data are collected from the forest department [20] and used for investigational analysis of forest fire detection with and without node or link failure using the combination rule PCR1 and PCR2. These forest data containing temperature and humidity collected by sensor nodes are used and the test results are analyzed using the MATLAB tool.

For the purpose of classification of forest fire, three classes namely Fire, Intermediate Fire and No Fire and four attributes namely Low Humidity, High Humidity, Low Temperature, High Temperature are taken as training and test dataset in the forest fire detection.

Using the combination rule PCR1 and PCR2, the output of masses from the three classifiers namely, Support Vector Machine signified by SVM, SVM Radial Basis Function (SVMRBF) (Sigma=0.3) and SVM Radial Basis Function (SVMRBF) (Sigma=0.9999) are combined and the results are analyzed in the background of link or node failure and without link or node failure in the communication system of the wireless sensor network used to detect fire in the forest.

Consider Θ = {F, IF, NF} with the following belief assignments for the dataset model without link or node failure. The masses generated from the classifier using SVM Polynomial are

m(F) = 0.28, m(IF) = 0.29, m(NF) = 0.06, m(F U IF) = 0.04, m(FUNF) = 0.23, m(IF U NF) = 0.09, m(FUIFUNF)=0.01

The masses generated from the classifier using SVMRBF (Sigma=0.3) are

m(F) = 0.25, m(IF) = 0.33, m(NF) = 0.01, m(F U IF) = 0.04, m(FUNF) = 0.19, m(IF U NF) = 0.17, m(FUIFUNF)=0.01

The masses generated from the classifier using SVMRBF (Sigma=0.9999) are

m(F) = 0.32, m(IF) = 0.22, m(NF) = 0.07, m(F U IF) = 0.06, m(FUNF) = 0.20, m(IF U NF) = 0.12, m(FUIFUNF)=0.01

From the above masses, the sum of all non-zero column sums of all non-empty sets, d_{12} is calculated to be 2 in case of PCR1 and the sum of all non-zero column sums of all non-empty sets only involved in the conflict, e_{12} is calculated to be 1.5 in case of PCR2. The basic belief mass function with the PCR1 rule of combination is calculated to be m_{PCR1}(F) = 0.42; m_{PCR1}(IF) = 0.32; m_{PCR1}(NF) = 0.06, m_{PCR1}(F U IF) = 0.02, m_{PCR1}(FUNF) = 0.12, m_{PCR1}(IFUNF) = 0.06, m_{PCR1}(FUIFUNF)= 0.01. The basic belief mass function with the PCR2 rule of combination is calculated to be m_{PCR2}(F) = 0.51; m_{PCR2}(IF) = 0.41; m_{PCR2}(NF) = 0.07, m_{PCR2}(F U IF) = 0, m_{PCR2}(FUNF) = 0.01, m_{PCR2}(IFUNF) = 0, m_{PCR2}(FUIFUNF)= 0.

Finally, using PCR1 rule, the accuracy is calculated to be Fire = 42%, Intermediate Fire = 32% and No Fire = 6% and the Conflict = 20%, whereas using PCR2 rule, the accuracy is calculated to be Fire = 51%, Intermediate Fire = 41% and No Fire = 7% and the Conflict = 1% as shown in the TABLE I.

Table 1. Accuracy of engines

Engine	Fire	Intermediate Fire	No Fire	Conflict
PCR1	42 %	32 %	6 %	20 %
PCR2	51 %	41 %	7 %	1 %

From the TABLE I it is concluded that the belief masses of PCR2 of all the three classes are more than that of PCR1. The conflict mass in respect of PCR2 is less than that of PCR1. Hence, it is affirmed that the PCR2 rule gives a better solution to the combination of conflict resources than PCR1in the case of forest fire detection.

From the figure 3 it is concluded that the accuracy of fire for the PCR2 engine is more than while comparing the input information resources, with that of PCR1 engine and the conflict is also reduced when using PCR2 rule than PCR1 rule.

Experimental Analysis of PCR1and PCR2 rule for failure in WSNs

Consider Θ = {F, IF, NF} with the following belief assignments. When there is link or node failure in the wireless sensor network, the masses generated from the classifier using SVM Polynomial are

m(F) = 0.56, m(IF) = 0, m(NF) = 0.06, m(F U IF) = 0.04, m(FUNF) = 0.23, m(IF U NF) = 0.09, m(FUIFUNF)=0.01

The masses generated from the classifier using SVMRBF (Sigma=0.3) are

m(F) = 0.25, m(IF) = 0.33, m(NF) = 0, m(F U IF) = 0.04, m(FUNF) = 0.19, m(IF U NF) = 0.17, m(FUIFUNF)=0.01

The masses generated from the classifier using SVMRBF (Sigma=0.9999) are

m(F) = 0.32, m(IF) = 0.22, m(NF) = 0.07, m(F U IF) = 0.06, m(FUNF) = 0.20, m(IF U NF) = 0.12, m(FUIFUNF)=0.01

From the above masses, the sum of all non-zero column sums of all non-empty sets, d_{12} is calculated to be 2 in case of PCR1 and the sum of all non-zero column sums of all non-empty sets only involved in the conflict, e_{12} is calculated to be 1.5 in case of PCR2. The basic belief mass function with the PCR1 rule of combination is calculated to be $m_{PCR1}(F)$ = 0.60; $m_{PCR1}(IF)$ = 0.16; $m_{PCR1}(NF)$ = 0.05, $m_{PCR1}(F\ U\ IF)$ = 0.02, $m_{PCR1}(FUNF)$ = 0.11, $m_{PCR1}(IFUNF)$ = 0.06, $m_{PCR1}(FUIFUNF)$= 0.01. The basic belief mass function with the PCR2 rule of combination is calculated to be $m_{PCR2}(F)$ = 0.74; $m_{PCR2}(IF)$ = 0.19; $m_{PCR2}(NF)$ = 0.06, $m_{PCR2}(F\ U\ IF)$ = 0, $m_{PCR2}(FUNF)$ = 0.01, $m_{PCR2}(IFUNF)$ = 0, $m_{PCR2}(FUIFUNF)$= 0.

Finally, using PCR1 rule, the accuracy is calculated to be Fire = 60%, Intermediate Fire = 16% and No Fire = 5% and the Conflict = 19%, whereas using PCR2 rule, the accuracy is calculated to be Fire = 74%, Intermediate Fire = 19% and No Fire = 6% and the Conflict = 1% as shown in the TABLE II.

Table 2. Accuracy of engines

Engine	Fire	Intermediate Fire	No Fire	Conflict
PCR1	60 %	16 %	5 %	19 %
PCR2	74 %	19 %	6 %	1 %

From the TABLE II it is determined that the belief masses of PCR2 of all the three classes are more than that of PCR1. The conflict mass in respect of PCR2 is less than that of PCR1. Hence, it is affirmed that the PCR2 rule gives a more efficient solution to the combination of conflict resources though there is link or node failure, than PCR1in the case of forest fire detection.

From the figure 4 it is approved that the accuracy of fire for the PCR2 engine is more accurate while comparing the input information resources in case of link or node failure, with that of PCR1 engine and the conflict is also reduced when using PCR2 rule than PCR1 rule.

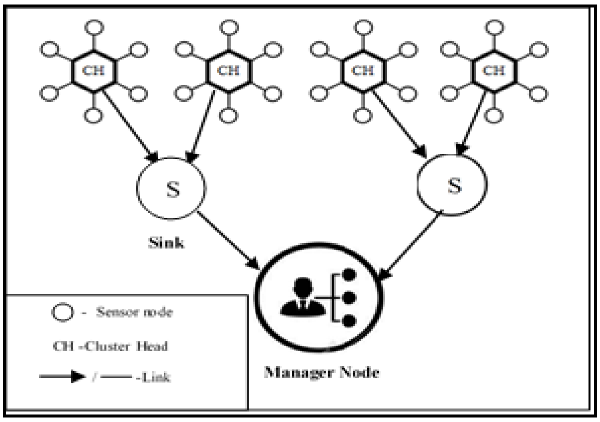

Figure 1. Architecture of Wireless Sensor Networks

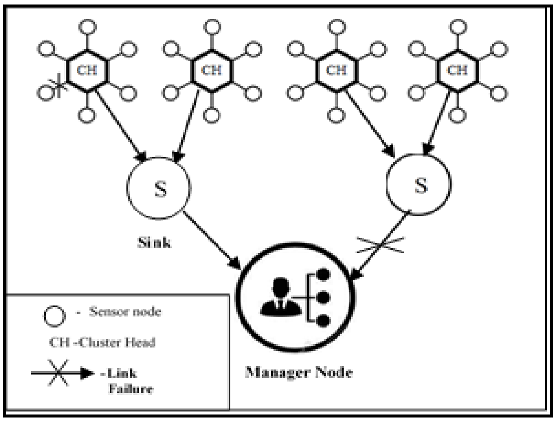

Figure 2. Link or node failure in Wireless Sensor Networks

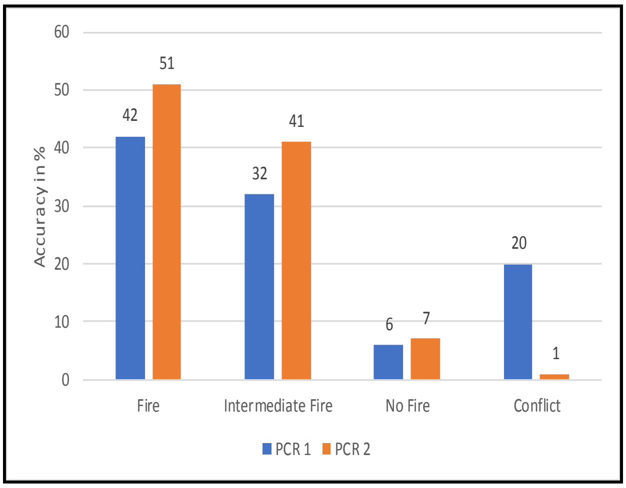

Figure 3. Comparison of PCR1 and PCR2

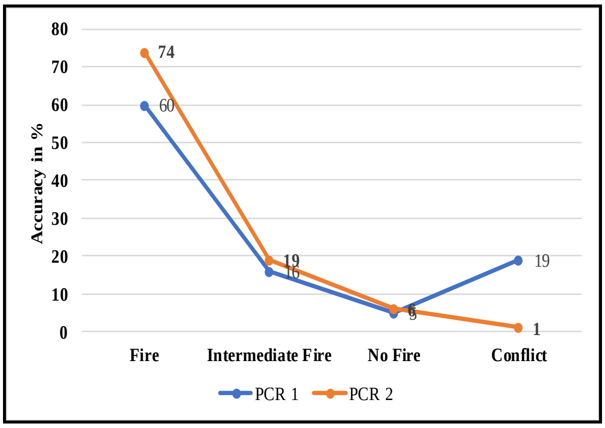

Figure 4. Comparison of PCR1 and PCR2 during network failure

CONCLUSION

In this paper a new evidence combination rule using PCR2 with more effective evidential conflict redistribution is envisioned. First, a new concept of evidence consensus and the conflict redistribution using PCR2 is computed from the basic belief masses assigned to each focal set in respect with original or local conflict masses. This PCR2 approach appears to be ideally suited for combination of bodies of evidence and is able to overcome the flaws of the preceding PCR1 and had demonstrated the effective and the performance of the PCR2 combination rule.

A very simple PCR1 rule and PCR2 rule have been proposed and compared for the same forest fire dataset. The PCR2 distributes the epistemic uncertainty in a precise manner than PCR1. The accuracy of belief masses of fire using PCR2 is higher than that of the PCR1 by around 9% by redistributing the conflicting masses to all the three classes. The percentage of conflict masses for the PCR2 is remarkably decreased by 19% than PCR1 thus redistributing the conflicting masses to the relevant classes of fire dataset.

In our second approach link or node failure in wireless sensor network is considered and experimental analysis are accomplished using PCR1 and PCR2 for the same forest fire dataset. The accuracy of belief masses of fire using PCR2 is higher than that of the PCR1 by around 14% by redistributing the conflicting masses to all the three classes. The percentage of conflict masses for the PCR2 is remarkably decreased by 18% than PCR1 thus redistributing the conflicting masses to the relevant classes of fire dataset.

Even a slight increase in the accuracy in this context of forest fire detection, it is no doubt that, there is an enormous savings in the affluence of the forest and the environment. But here an appreciable increase in the accuracy by PCR2 has been achieved for the same forest fire dataset. In the context of PCR1 and PCR2, considering with or without link failure the performance of PCR2 surpasses the performances of PCR1. From the above it is perceived that PCR2 is highly suitable for forest fire detection. The forest data is better appreciated over obscurity and exactitude, while using the proportional conflict redistribution rule 2.

REFERENCE

[1] M.D. Flannigan, B.J Stocks & B.M Wotton, 2000. Climate change and forest fires:, Science of The Total Environment, Volume 262, Issue 3, 15 November 2000, Pages 221–229, www.elsevier.com/locate/scitotenv

[2] Raghavendra, C.; Sivalingam, K.; Znati, T. Wireless Sensor Networks. Springer: New York, NY, USA, 2004.

[3] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," Computer Networks, vol. 38, pp. 393-422, 2002.

[4] Y. Aslan, A framework for the use of wireless sensor networks in the forest fire detection and monitoring [M.S. thesis], Department of Computer Engineering, The Institute of Engineering and Science Bilkent University, 2010.

[5] Culler, D.; Estrin, D.; Srivastava, M. Overview of sensor networks. IEEE Comput. 2004, 37, 41–49.

[6] S. Park, H. Park, E. Lee, and S.-H. Kim, "Reliable and flexible detection of large-scale phenomena on wireless sensor networks," IEEE Communications Letters, vol. 16, no. 6, pp. 933–936, 2012.

[7] M. Hefeeda and M. Bagheri, "Forest fire modeling and early detection using wireless sensor networks," Ad-Hoc and Sensor Wireless Networks, vol. 7, no. 3-4, pp. 169–224, 2009.

[8] J. Lloret, M. Garcia, D. Bri, and S. Sendra, "A wireless sensor network deployment for rural and forest fire detection and verification," Sensors, vol. 9, no. 11, pp. 8722–8747, 2009.

[9] Abidha T E, Paul P Mathai, "Reducing False Alarms in Vision Based Fire Detection with NB Classifier in EADF Framework", International Journal of Scientific and Research Publications, Volume 3, Issue 8, August 2013, ISSN 2250-3153.

[10] Rachna Raghuwanshi, " A Comparative Study of Classification Techniques for Fire Data Set", International Journal of Computer Science and Information Technologies, Vol. 7 (1) , 2016, 78-82, ISSN:0975-9646.

[11] Q. Chen, K.-Y. Lam, and P. Fan, "Comments on "Distributed Bayesian algorithms for fault-tolerant event region detection in wireless sensor networks"," IEEE Transactions on Computers, vol. 54, no. 9, pp. 1182–1183, 2005.

[12] P. P. Jayaraman, A. Zaslavsky, and J. Delsing, "Intelligent processing of k-nearest neighbors queries using mobile data collectors in a location aware 3D wireless sensor network," in Trends in Applied Intelligent Systems. Springer, 2010, pp. 260–270.

[13] Roshani.M.Bhave,"Recovery of node failure in wireless sensor networks using CASER Protocol and

DARA:Review”,International journal on Recent and Innovations trends in computing and communication, Volume 3,Issue 2, ISSN:2321-8169, 2004.

[14] Wang, T.Y.; Chang, L.Y.; Dun, D.R.; Wu, J.Y. Distributed fault-tolerant detection via sensor fault detection in sensor networks. In Proceedings of the IEEE 10th International Conference on Information Fusion, Quebec, Canada, 2007; pp. 1-6.

[15] W. Dong, Y. Liu, Y. He, T. Zhu, and C. Chen, “Measurement and analysis on the packet delivery performance in a large-scale sensor network,” IEEE/ACM Trans. Netw., vol. 22, no. 6, pp. 1952–1963, Dec. 2014.

[16] Daniel M., Distribution of Contradictive Belief Masses in Combination of Belief Functions, Inf., Uncert. and Fusion, Bouchon-Meunier, Yager and Zadeh (Eds.), Kluwer Acad. Publ., 2000, pp. 431-446.

[17] M. Daniel, “Associativity in combination of belief functions; a derivation of minc combination.” Soft Comput., pp. 288–296, 2003.

[18] Florentin Smarandache, Jean Dezert, Proportional Conflict Redistribution Rules for Information Fusion, Proceedings of the 8th International Conference on Information Fusion, Philadelphia, 25 - 29 July, 2005; IEEE Catalog Number : 05EX1120C, ISBN: 0-7803-9287-6.

[19] A. Martin and C. Osswald, A new generalization of the proportional conflict redistribution rule stable in terms of decision, CoRR, vol. abs/0806.1797, 2008.

[20] http://modis.gsfc.nasa.gov/MODIS Web.