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# Wireless Sensor Network Pre-Deployment Algorithm for Reliable Forest Fire Detection

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*Abstract*— **Forest fires are amongst the significant causes threatening our environment degradation nowadays. Current fire detection systems lack the capability of fire triggering detection from its early stages. Wireless sensor networks (WSN) as a solution letting to gather sensory data measurements, such as humidity and temperature, from all points of forest continuously, and, provide reliable and dependable data transmission to the control center. However, sensor networks face serious drawbacks such as its limited energy resources and the potential fault vulnerability due to cruel environmental conditions. Our framework includes proposals for a pre-deployment algorithm based Bayesian approach allowing determining the optimal parameters required to pre-deploy the WSN while achieving its fault detection. In our work, the sensor fault probability (the fact that the sensor itself can be defected) is introduced into the event detection process. For the Bayesian approach principle the optimal detection error resulting on both measurement error and sensor fault is exponentially decreased when the sensor neighborhood size increases. For a given detection error upper bound which resumes the fault tolerance in the WSN a minimum neighborhood size does exist. Through extensive simulations, we show that our proposed algorithm can provide a best choice of pre deployment parameters ensuring the WSN fault detection reliability while minimizing energy consumption.**

***Keywords--- Wireless Sensor Networks; Forest fire detection; Energy minimization; Bayesian approach; Sensor nodes pre-deployment; Reliable fault detection.***

## I. Introduction

Forest fires are amongst the most serious natural disasters on the Earth. It can cause multidimensional negative effects on the human life and the ecological level. Forest inflammation probability is increasingly worse due to daily human life activities and atmospheric changes. This disaster requires the usage of different forest fires detection techniques to prevent its development from its early stages.

The improvement of hazardous forests fires detection methods is becoming more sophisticated by the integration of new technologies. Traditional monitoring techniques used for forests fires detection are explained by [1] "guard towers to fire Located high points" and [2] "Osborne fire Finder" which shows a tool using a topographic printed map on a graduated disk. These techniques are considered as primary and unreliable view to the absence of a human side monitoring [3]. In an ameliorative framework, several researchers referred to WSN utilization such as [4], [5] and [6]. [7] presents a general framework for a wireless sensor network to be used in order to monitor the forest fire. They consider wireless sensor network life cycle of forest fire detection system. In their work the proposed system regards the sensor nodes low energy capacity and the difficult conditions of the environment which can involve the network reliability. Ref [8] used wireless sensor networks to improve the reliance, efficiency and effectiveness of rescuers in all phases in a tunnel fire event, due to best accuracy of information.

Wireless sensor networks have also been used for monitoring inaccessible environments by detecting unexpected events threatening the overall operation of the wireless sensor network , [9] [10]. Therefore WSN must distinguish the data due to the presence of a disruptive event from others data. Several researchers such as [11], [12], [13], [14] and [15] have studied the WSN fault detection methods, some of them have used the fault tolerant detection notion. This concept allows Wireless sensor network reliable operation even when one of its sensors is no longer works properly. It can be defined for the whole wireless sensor network that translates network capacity to act against the various sensors defect without inhibiting the execution of its task. This ability mainly depends on the environment deployment, the application type, the sensors characteristics and the sensor nodes to be used.

In this case, a wireless sensor network equipment could be deployed in order to detect hazardous event and more particularly forest fires. A big number of wireless sensor nodes will be pre-deployed in the forest. Each one will gather different data types such as humidity, temperature... All collected data will be sent to a sink node, which allow the transmission to the control center.

Our aim in this paper is to suggest a WSN pre-deployment solution ensuring a reliable forest fires detection using the Bayesian approach. This approach can provide an energy minimization algorithm ensuring best sensors nodes pre-deployment while offering tolerant WSN fault detection. The energy minimization comes from the algorithm ability to find the optimum sensors neighbors' size. In fact this sensors neighbors' size reduction will allow to communication volume minimization during the fault correction scheme. In this work the fact that the sensor itself can be faulty was taken into account by introducing the fault sensor probability into the fault detection algorithm. The proposed guarantees a best quality of fault detection method for a given detection error bound. This boundary represents the fault tolerance notion to be considered in the wireless network pre-deployment algorithm.

The reminder of this paper is organized as follows. Section 2 presents the practical framework of forest fire detection using the Bayesian approach characteristics. Section 3 describes the adopted methodology "the Bayesian approach principle". Section 4 presents our experimental results. Finally, Section 5 concludes the paper and provides future work discussion.

## II. PRACTICAL FRAMEWORK

In this work we will adopt a suitable forest fires detection system, which is appropriate to find the best sensor nodes size to be pre-deployed in a threatened environment especially during summer seasons.

Figure 1. A forest crossed by a river

Figure 1, represents a forest crossed by a river. This river reduces the fire risk in his sides. While moving away from this river, the possibility that a fire will trigger increases especially when temperature rises up in summer. Figure 2 shows a triggered fire which should be detected from its early stages. To better explain the practical framework for the Bayesian approach use, we need to adjust its parameters in the case of forest fires detection.

Figure 2. A forest triggered fire which should be detected from its early stages

The next parameters characterized the Bayesian approach algorithm. They are the algorithm output data ensuring the reliable deployment of the wireless sensor network in the forest:

$\tau_{opt}$ : ensuring distinguishing between the detection probability (about the presence of a fire in the forest) and the false alarm probability. It is called "common threshold" and it is used for all deployed sensor nodes. It is element letting to generate the alarm signal in the node when there is an event (fire) and allowing the Alarm packet routing to the control station.

$n_{opt}$ : The optimum sensors neighbors' size allowing the best quality of fault detection method in the wireless network (to be deployed in the forest) while providing the least energy consumption.

$k_{opt}$ : is called "majority vote parameter", which is a "key to ride" referring to the majority of sensor nodes' event decision and using their fusion into a collective data by the ( $k$ -out-of-$n$ ) rule letting the WSN to take an efficient decision about the abnormal event appearing in it.

The group of the algorithm input data that we mention below, letting us to have the previously cited parameters:

$P_f$ : is a probability that resume the sensor node bad behavior. And it's called "The sensor fault probability".

$P_0$ : is a probability denoting the absence of a fire in the forest. It's called "the, a prior, probability about the absence of an abnormal event".

$P_1$ : is a probability denoting the presence of a fire in the forest. It's called "the, a prior, probability about the presence of an abnormal event".

Since the river reduces the fire risk in his sides, then when we are near its board we should choose $P_0 > P_1$ .

While moving away from this river, the possibility that a fire will trigger increases, then we should choose $P_0 < P_1$ (as it's shown in figure 3).

$P^n_{e,bound}$ : is the detection error probability boundary value. This probability can be tolerated according to the deployment field of the WSN. For example, in the forest fire detection case, we can be a little bit tolerant about this value when we are in the river sides', unless when we are far away the river sides', we required a near zero choice of the $P^n_{e,bound}$ value.

$n_{\max}$ : is the neighborhoods maximum size of nodes to be deployed in the different forest areas.

As we've said previously, the Bayesian approach requires many important parameters allowing its application on practical framework. And we remind here that $P_f$ is the sensor node fault probability resuming its bad behavior.

The two cases of choice related to the, a prior, probabilities about the presence or the absence of a fire in the forest (abnormal event) ( $P_0 > P_1$ or $P_0 < P_1$ ) are shown in figure 3.

The area surrounded by a blue circle designates the river sides' then we have $P_0 > P_1$ .

The area surrounded by a red circle designates the river faraway areas' => a potential dangerous of fire triggering can occur in those areas => then a serious attention should be paid to avoid such a disregarded consequence.

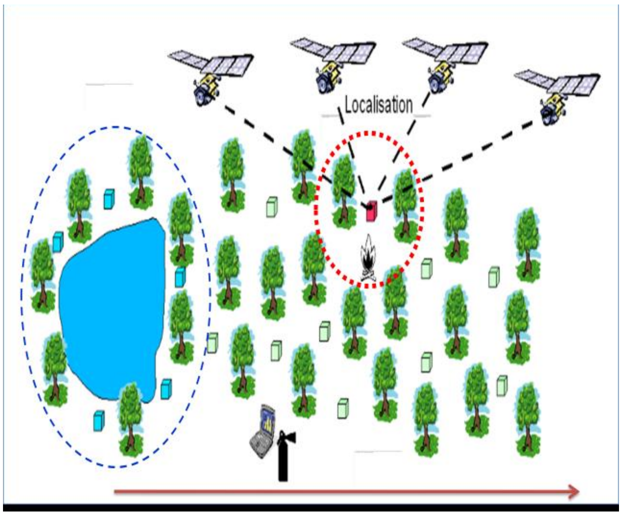


Figure 3. Choice of the, a prior, probability basing on the position away the river sides'

## III. BAYESIAN APPROACH

The Bayesian approach was firstly used and explained by [13]. It had been the best mechanism that boosted us to employ its characteristics as a basic tool to make the sensor nodes' pre-deployment possible.

This method has appeared as the right path to cross in our work seeing that it allows the least energy consumption and the best fault tolerant detection. Indeed, it's considered as the pioneer approach that we can use to propose a WSN pre-deployment algorithm for forest fire detection. This character came out from the fact that the Bayesian approach provides the required and the important deployment parameters. The sensor nodes will be glued upon trees as shown in figure 4. The choice of the best number of sensor nodes to be glowed upon trees is the aim of the pre-deployment algorithm.

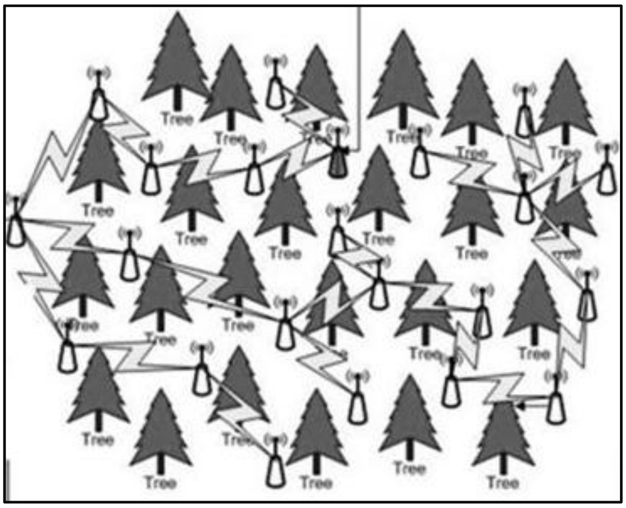

Figure 4. Sensor nodes glued upon trees

### *A. Bayesian approach principle:*

The Bayesian approach principle is based on a hypothetical test about the presence or absence of a particular event resumed respectively on the hypotheses couple denoted $H_1$ (meaning the presence of the abnormal event) and $H_0$ (meaning the absence of the abnormal event) in a particular WSN region (considered as area of event). The possibilities of $H_1$ and $H_0$ are resumed in the, a prior, probabilities $P_1$ and $P_0$ In this approach [15] has considered a detection system with two layers. It includes $n$ sensors and a fusion sensor as shown in figure 5. We denote that the sensor observations $x_i$ ( $i = 1,...,n$ ) are identically distributed and independent. They allow giving the unknown binary hypothesis employed for all sensors in order to obtain $n$ binary decisions $u_i$ . Those decisions will be combined to make a final decision $u_0$ at the fusion sensor. [13] and [16] proved that the adopted detection process is considered as very reliable.

Once $H_j$ is true, $x_i$ will follow the probability distribution function $p(x_i \backslash H_j), j = 0,1$ . $u_i$ Designates the binary decision (0 or 1) of the $i$ sensor, and it represents the likelihood ratio threshold test output.

$$\frac{p(x_i \backslash H_1)}{p(x_i \backslash H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \qquad (1)$$

$\lambda$ is the common threshold test used for all sensor nodes. Every sensor node $S_i$ takes a proper decision $u_i$ on the basis of a comparison with the likelihood ratio threshold, after that all those decisions will be independently transmitted to the fusion center. This fusion sensor is the responsible element of making a final decision $u_0$ according to the fusion rule, « $k$-out-of-$n$ rule», or also majority vote rule. This voting method allows taking the final decisions about the presence or absence of a particular event. The fusion rule is:

$$u_0 = \begin{cases} 1, \text{if } u_1 + ... + u_n \geq k \text{:the fusion sensor decides } H_1 \\ 0, \text{if } u_1 + ... + u_n < k \text{:the fusion sensor decides } H_0 \end{cases}$$

We denote that $k$ is between 1 and $n$. The decision taken by the fusion sensor is the same taken by the majority $k$ among the $n$ sensors.

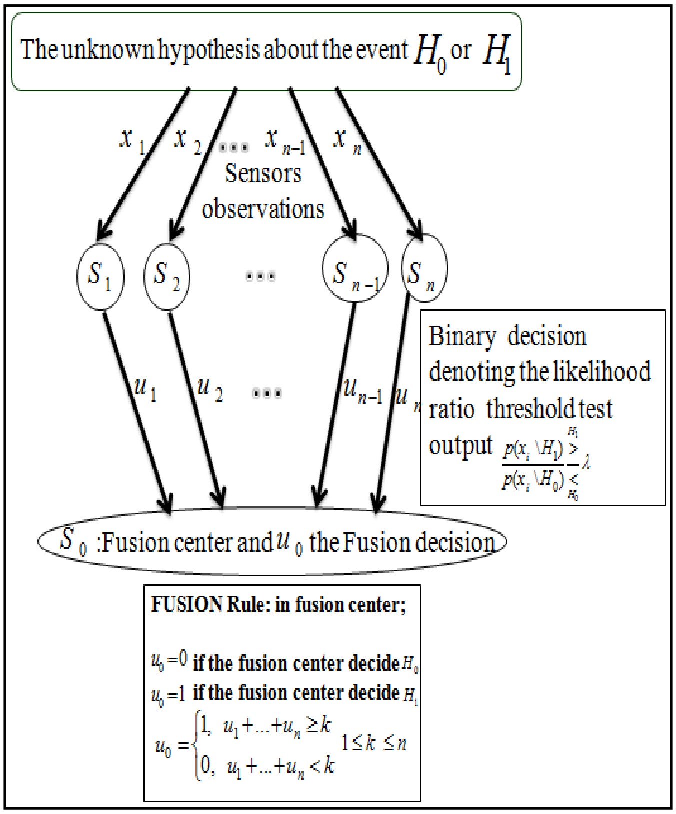


Figure 5. The Bayesian approach principle

In order to optimize the $k$ parameter we eager to make its choice using the absolute majority vote principle which is well explained in [17].

$$k = \begin{cases} \frac{n}{2} \text{ if } n \text{ is an even number} \\ \frac{n+1}{2} \text{ if } n \text{ is an odd number} \end{cases}$$

The importance of the optimization of the $k$ parameter will be clearer later while introducing the WSN energy optimization notion.

### B. *Error detection probability calculation steps:*

In the following steps a fault sensor probability $P_f$ $(= \beta + \gamma)$ will be introduced in the fault detection scheme. It ensures to take into account the sensor nodes bad behavior.

$\beta$ : Denotes the fault sensor probability, type $I$ : An event is not detected and the decision is converted to "event detected", due to sensor failure.

$\gamma$ : Denotes the fault sensor probability, type $II$ : An event is detected and the decision is initially "event detected".

For all sensors, $\tilde{P}_F$ and $\tilde{P}_D$ denoting respectively the probability of false alarm and the probability of detection after considering the occurrence of the sensor fault. We will have:

$$\begin{aligned} \tilde{P}_F &= P_F + \beta(1-P_F) - \gamma P_F \\ &= P_F(1-P_f) + \beta \end{aligned} \qquad (2)$$

And

$$\begin{aligned} \tilde{P}_D &= P_D + \beta(1-P_D) - \gamma P_D \\ &= P_D(1-P_f) + \beta \end{aligned} \qquad (3)$$

We indicate that

$P_F = p(u_i = 1 \backslash H_0)$ And $P_D = p(u_i = 1 \backslash H_1)$

With no loss of generality, we denote that $\beta = \gamma = \frac{1}{2} P_f$

Where we can write:

$$\tilde{P}_F = P_F(1-P_f) + \frac{1}{2} P_f \qquad (4)$$

$$\tilde{P}_D = P_D(1-P_f) + \frac{1}{2} P_f \qquad (5)$$

These two probabilities represent the detection transmission model limits as summed up in Figure 6.

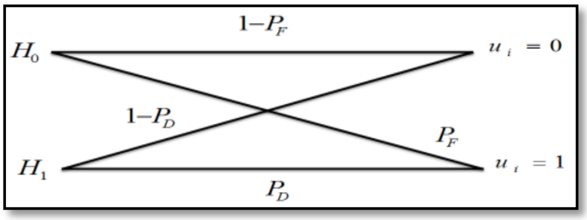


Figure 6. The detection transmission model limits

The fusion decision ($u_0$) quality is evaluated by the WSN detection probability ($\tilde{Q}_D$) and the WSN false alarm probability ($\tilde{Q}_F$). These probabilities are given by:

$$\tilde{Q}_F = \sum_{i=k}^{n} C_i^n \tilde{P}_F^i (1-\tilde{P}_F)^{n-i} \quad (6)$$

$$\tilde{Q}_D = \sum_{i=k}^{n} C_i^n \tilde{P}_D^i (1-\tilde{P}_D)^{n-i} \quad (7)$$

The error detection probability $\tilde{P}_e^n$ is given by $\tilde{P}_e^n = P_0\tilde{Q}_F + P_1(1-\tilde{Q}_D)$ and our aim is its minimization. Where $P_0$ and $P_1$ are the, a prior, probabilities of $H_0$ and $H_1$.

The distributed detection purpose firstly to find the optimal thresholds $(\lambda, k)$ or also $(\tau, k)$ where $\tau = \ln\lambda$ for each sensor node, while fixing the, a prior probabilities about the event, $P_0$ and $P_1$. Then the neighborhood size $n$ is generally determined by the maximum sensor node communication radius. [18] Have solved this problem in proposing the following theorem: For fixed $n$ and $k$, the error detection probability $\tilde{P}_e^n$ is a quasi-convex function of $\lambda$ and reached its single minimum for $\lambda_{opt}$.

## IV. FOR WSN PRE-DEPLOYMENT ALGORITHM

This section will cover a few scenarios helping us to choose the maximum neighbors size $n_{\max}$ and the relationship between $k_{opt}$ and $n_{opt}$ allowing proving the majority vote rule (resuming that $k_{opt}$ is related to the $n_{opt}$ choice). Then we present the pre-deployment algorithm and discuss its simulations results'.

### *A. Some simulation scenario's for parameters choice*

This first part of simulations aims to find the best neighbors' sensor size providing the error detection probability minimization. The Figure 7 illustrates the $\tilde{P}_{e,\min}^n$ curve evolution in function of the neighbors' sensor size $n$. While analyzing this curve we can observe the $\tilde{P}_{e,\min}^n$ convergence to the null value exponentially. This convergence improves the Chernoff Theorem Lemma [19]. The determination of the optimal neighbors' size $n_{opt}$ requires an increase of $n$ as it is shown in figure 7. The determination of $n_{opt}$ optimal value will ensure the minimization of the WSN energy consumption while the detection performance is demonstrated by $\tilde{P}_{e,\min}^n$ convergence to the null value.

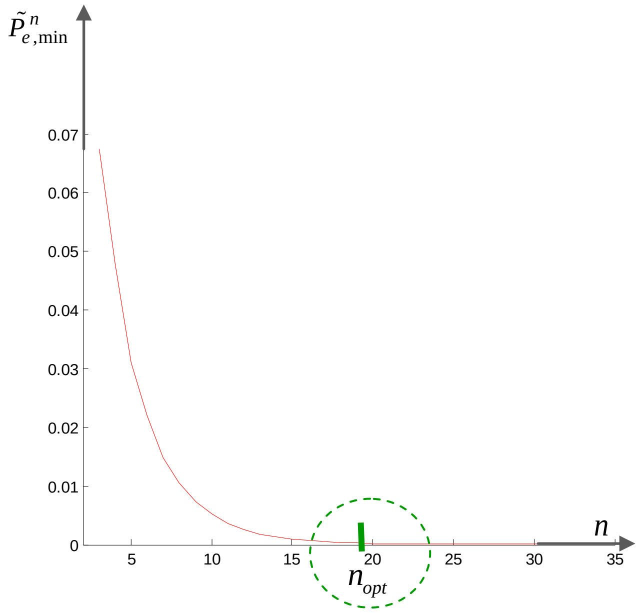


Figure7. Convergence of $\tilde{P}_{e,\min}^n$ to the null value.

In this second part of simulations we aim to find the optimal $(n_{opt}, k_{opt})$ values best choice. For this reason a study of the $\tilde{P}_{e,\min}^n$ evolution in function of neighbors' size $n$ is required. In figure 7 the simulation was done for a "new sensor node" where its fault probability $P_f = 0$ but in figure 8 we aim to study the influence of sensor fault probability on the $\tilde{P}_{e,\min}^n$ convergence. Figure 8 shows that when $P_f$ increases the $n$ size required for $\tilde{P}_{e,\min}^n$ convergence to the null value increases. The value ensuring the $\tilde{P}_{e,\min}^n$ convergence is $n_{opt}$ depending on $P_f$. Aiming to study the $P_f$ impact on $\tilde{P}_{e,\min}^n$, we've plotted $\tilde{P}_{e,\min}^n = f(n)$ with different $P_f$ values cases'. Analyzing figure 8 we can note that when $\tilde{P}_{e,\min}^n$ converges to the null value then a proportional $n_{opt}$ value can be selected. This estimative choice has to be a little bit lower than $n_{\max}$ which represent an algorithm input to be used in the pre-deployment algorithm.

In this third part we aim to determinate the majority vote parameter $k_{opt}$ which is relative to the $n_{opt}$ value, thus an outlined above "absolute majority vote" rule was used. Simulation shown in Figure 9 was made by changing $k$ and $n$ parameters in order to justify our algorithm voting rule use.

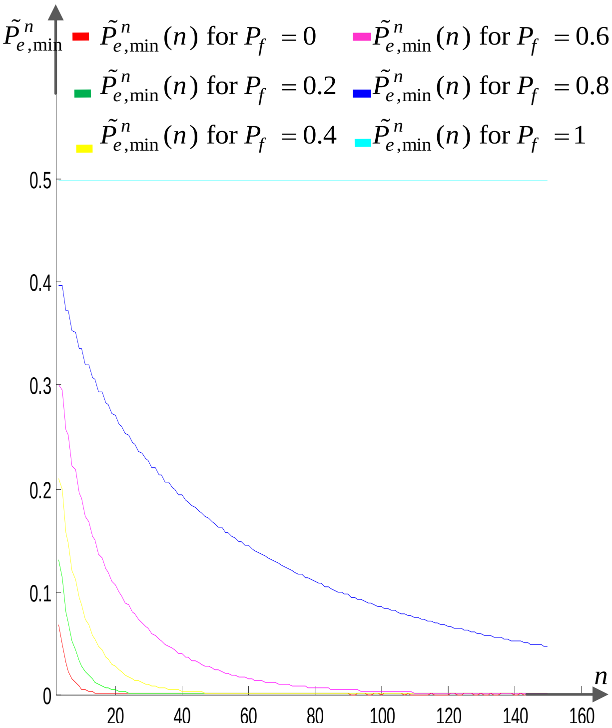


Figure 8. Convergence of $\tilde{P}^n_{e,\min}(n)$ to the null value for different $P_f$ .

By examining the $\tilde{P}^n_e$ curves in function of $\tau$ for $P_0 = P_1$ we can notice that an arbitrary choice of $n$ and $k$ causes the remoteness of $\tau$ from the best threshold test value (the null value in case of $P_0 = P_1$ ).

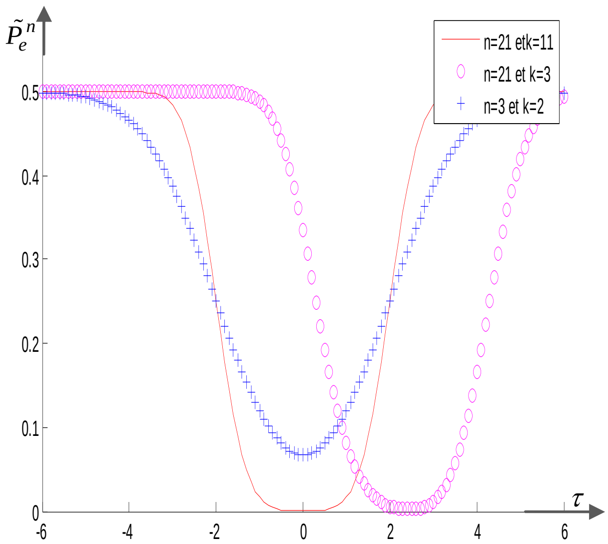


Figure 9. $\tilde{P}^n_e$ Curve for different choice of $n$ and $k$ .

Thus we note that the curves reaching their minimum for $\tau_{opt}$ are those plotted when (n=21,k=11) and (n=3,k=2) meaning that the majority vote rule is ensured by $k = \frac{n+1}{2}$.

We can therefore conclude that the majority voting rule should be used in our algorithm to avoid the determination lost of $\tau_{opt}$ as it is shown for (n=21 and k=2).

## *B. Pre-deployment algorithm*

The sensor nodes' deployment will be ensured by a set of parameters "the algorithm outputs" $(n_{opt}, k_{opt}, \tau_{opt})$ known also as "the optimum triple". This pre-deployment algorithm will ensure a WSN reliable fault tolerant detection. The signification of our algorithm inputs/outputs are well explained previously. All previous simulations scenarios lead to deduce the variation impact of $P_0, P_1, P^n_{e,bound}, P_f$ on the optimum triplet $(n_{opt}, k_{opt}, \tau_{opt})$ that we want to compute. In fact the $n_{opt}$ determination is condemned by $n_{\max}$ choice which is well explained in the first simulations part. In the case when $\tilde{P}^n_{e,\min} \geq P_{e,bound}$ , the algorithm should stop and gives us the outputs $\tau_{opt}$ , $k_{opt}$ and $n_{opt}$ ; otherwise, $n$ should be initialized at $n_{\max}$ , the best appropriate choice of $n = n_{\max}$ is done using a perceptive study as it is shown in figure 8. The proposed algorithm ensure the determination of the optimum triplet $\tau_{opt}$ , $k_{opt}$ and $n_{opt}$ . The following sequences illustrate our pre-deployment algorithm in detail.

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The algorithm Inputs are: $P_0$ , $P_1$ , $P^n_{e,bound}$ , $P_f$ and $n_{\max}$ (should be fixed in each iteration).
And the algorithm Outputs are: $\tau_{opt}$ , $k_{opt}$ and $n_{opt}$ (that we aim to compute).

$n \leftarrow 1$
**B:**
$i \leftarrow 0$
**A:**
For all $\tau$
{
$\tilde{P}^n_e(i) \leftarrow func\_\text{calc\_}\tilde{P}^n_e(\tau, \text{n}, \text{P}_0, \text{P}_1, P_f)$
}
$i \leftarrow i + 1$
$if\ (i \prec n_{\max})$ go to **A**
$\tilde{P}^n_{e,\min} \leftarrow \underset{i}{MIN}(\tilde{P}^n_e(i))$
$if\ (\tilde{P}^n_{e,\min} \prec P^n_{e,bound})$
{
$n = n + 1$
go to **B**
}

$n_{opt} \leftarrow n$

$if\ (n_{opt} \bmod 2) = 0; k_{opt} = \frac{n_{opt}}{2}$

$Else; k_{opt} = \frac{n_{opt}+1}{2}$

$\tau_{opt} \leftarrow func\_calc\_\tau_{opt}(n_{opt}, P_0, P_1, P^n_{e,bound})$

The main pre-deployment algorithm uses two functions; the first one allows calculating $\tilde{P}_e^n$ in the case of $P_f$ presence. All calculations steps used in this algorithm are well explained in section III.B. The second function aims to calculate $\tau_{opt}$ for the $\tilde{P}_e^n$ 's minimal value with the least of steps. The function used to determine $\tau_{opt}$ represents a sampling tools of the $\tau$ values using a reduced sampling rate as it is well explained by figure 10 ($\tau$ is responsible of the sensor decision distinguishing the false alarm probability from the detection one). A reduced sampling rate of the $\tau$ values ensures the determination of the most suitable threshold $\tau_{opt}$ .

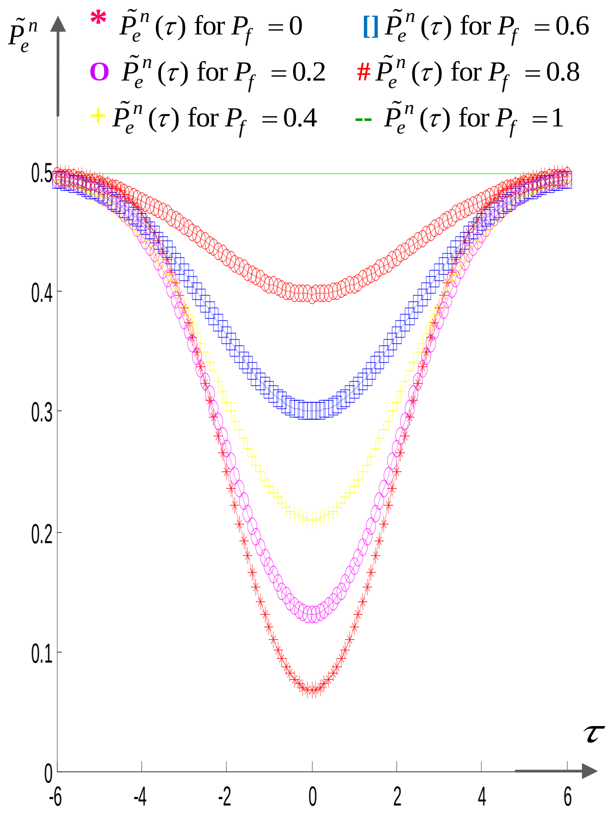


Figure 10. $\tilde{P}_e^n(\tau)$ Curve for different $P_f$ .

All results of pre-deployment algorithm ensuring WSN fault detection are shown in (table I). We can deduce that when $P^n_{e,bound}$ value increases fault detection in WSN will be more faults tolerant, where the sensor neighbors' size $n_{opt}$ required for the pre-deployment will be reduced. A refined $P^n_{e,bound}$ value requires a big sensors neighbor's size $n_{opt}$ . An increasing value of $P_f$ requires the use of a big neighbors' sensor size. Thus we propose an appropriate solution by choosing a $P^n_{e,bound}$ highest value, and thus we can use such sensor in special forest areas which does not require a zero value of the minimum detection error probability such as the nearest boundaries of the river. The value taken by $\tau_{opt}$ depends on the, a priori, probabilities $P_0$ and $P_1$ . It aims to distinguishing the sensor detection probability from the sensor false alarm.

TABLE I
THE WSN PRE-DEPLOYMENT ALGORITHM RESULTS

| $P_f$ | $n_{max}$ | $P_0$ | $P_1$ | $P^n_{e,bound}$ | $\tau_{opt}$ | $k_{opt}$ | $n_{opt}$ |
|---|---|---|---|---|---|---|---|
| 0 | 20 | 0.5 | 0.5 | 0.001 | **0** | **8** | **15** |
| 0.1 | 50 | 0.5 | 0.5 | 0.00001 | **0.112** | **20** | **39** |
| 0.2 | 50 | 0.5 | 0.5 | 0.0001 | **0.068** | **20** | **39** |
| 0. 2 | 60 | 0.5 | 0.5 | 0.00001 | **0.030** | **21** | **41** |
| 0.3 | 80 | 0.5 | 0.5 | 0.00001 | **0.104** | **21** | **41** |
| 0.3 | 50 | 0.25 | 0.75 | 0.001 | **0.107** | **18** | **35** |
| 0.3 | 50 | 0.75 | 0.25 | 0.001 | **0.340** | **18** | **35** |
| 0.4 | 100 | 0.5 | 0.5 | 0.0001 | **0.103** | **50** | **99** |
| 0.5 | 200 | 0.5 | 0.5 | 0.00001 | **0** | **74** | **147** |
| 0.7 | 200 | 0.5 | 0.5 | 0.01 | **0.114** | **100** | **199** |
| 0.7 | 50 | 0.5 | 0.5 | 0.1 | **0.210** | **105** | **209** |
| 0.8 | 100 | 0.25 | 0.75 | 0.1 | **0.292** | **111** | **221** |

## V. CONCLUSION

Forest fires detection using WSN seems to be a good solution for a reliable preventive system arresting fire triggering from its early stages. This study firstly proposes a practical framework for the Bayesian approach in order to pre-deploy the WSN in different forest areas', while guaranteeing events detection. Secondly, we have explained the Bayesian approach principle resumed in a distributed faults detection scheme having a certain level of performance and fault tolerance. This approach is based on a set of probabilities and optimal parameters ensuring the WSN pre-deployment while conserving energy. Finally, in order to find these optimal parameters we proposed an algorithmic tool "the pre-deployment algorithm". The proposed algorithm is based on a set of inputs parameters adjustable according to deployment areas. These inputs influence the values to be taken by the optimal parameters that we reach to compute as outputs.

As a perspective this work can be experimentally validated by a WSN real platform pre deployment in a forest crossed by a river.

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