

Localisation of Forest Fires by RFID Sensors Based on RSSI/AoA Combined with ANN

Konan Fernand Gbamele^{a,*} , Gnléba Célestin Bogui^b and N'Golo Mamadou Kone^c

^aFélix Houphouët-Boigny National Polytechnic Institute, Yamoussoukro, Ivory Coast

^bSan Pedro Polytechnic University, San Pedro, Ivory Coast

^cFélix Houphouët-Boigny University, Ivory Coast

Abstract

Every year, African countries face the tragic loss of life and destruction of natural and personal property due to forest fires. This issue has been the subject of research for many years in an effort to find a solution. This article aims to study the application of 3D multilateration positioning based on a hybrid of received signal strength indicator (RSSI) and angle of arrival (AoA) (RSSI/AoA) using an artificial neural network (ANN) to optimise the position of Radio Frequency Identification (RFID) sensors for forest fire prevention/detection. The first approach is based on the most commonly used radio measurement techniques, such as the hybrid RSSI/AoA technique based on the linear least squares (LLS) method to find a solution that minimises the error in the position of the RFID reader. The second approach presents a method using an RNA to correct the observed RSSI/AoA measurements, thereby aiming to locate RFID sensors in forests where obstacles are present and may influence signals. The simulation results of the RNN model show the best performance, achieving a location error of 0.2208m using four RFID sensors. This research highlights the importance of selecting artificial intelligence models for monitoring forest fires around the world.

Keywords: Climate; Fire; RFID; Drought, ANN.

1. Introduction

Forest fires are a frequent occurrence around the world and contribute to climate change, causing significant economic losses and ecological destruction [1]. Forest fires can be caused by natural phenomena or human actions. The scale, intensity and duration of forest fires have continued to increase in recent years [2]. Climate change will continue to increase the risk of forest fires worldwide due to prolonged hot and dry periods. One of the causes is the reduction of forests due to forest fires, which exacerbates the impact of global warming [3]. In addition, forest fires are unpredictable and uncontrolled, posing a serious threat to the lives of communities [4]. These forest fires cause erosion that can lead to flooding and landslides, threatening the lives of local populations. Forest fires can occur as a result of climate change and cause significant environmental damage. It is therefore essential to identify forest fire detection as one of the dynamic challenges of environmental management. The need to observe, remotely monitor and retrieve data from a complex and distributed environment is growing rapidly, especially with recent advances in Internet of Things (IoT)

* Corresponding author.

E-mail address: konan.gbamele@inphb.ci

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technologies using sensor networks in recent decades. In this type of network, sensors exchange information about the environment in order to establish an overall view of the monitored area. The sensors are miniaturized autonomous systems equipped with a data processing and storage unit and a wireless transmission unit, which may or may not be battery-powered. The sensors (or nodes) in a sensor network collect information on factors such as temperature changes, movements, vibrations, humidity, etc. Advances in wireless technologies, such as wireless sensor networks (WSNs), have contributed to the development of IoT solutions for a number of industrial sectors. Additional technologies and devices, such as barcodes, smartphones, social networks, IPv6, mobile communication, radio frequency identification (RFID), Wi-Fi, WiMax, and cloud computing, support IoT applications [5]. RFID is essential to building the IoT, which is important for promoting the flourishing development of next-generation information technology. RFID sensors are widely used in many areas of identification due to their contactless nature, low power consumption, and the speed with which they can recognize targets. RFID technology has emerged as a transformative force and has made substantial inroads into the forestry sector, where it is catalyzing revolutionary advances in forest management practices [6]. A system using RFID temperature sensors could support early and rapid response to forest fires, saving lives and reducing damage.

Although RFID technology has demonstrated great potential in various applications, its adoption for forest fire detection is relatively limited. Research is underway to fully explore the potential of RFID technology, including the use of RFID sensors, for effective fire detection in these environments. The lack of reliable and effective forest fire detection systems makes RFID technology a more reliable and effective system, capable of accurately detecting fires in real time. RFID is one of the assets for solving problems such as high false alarm rates, long response times and limited coverage. In addition to the lack of detection systems, there are also issues with limited or unreliable network connectivity, environmental factors affecting the accuracy of fire detection, and integration with emergency response systems, which further complicate the deployment of energy-efficient fire detection systems [7]. Furthermore, energy constraints in remote areas further complicate the deployment of energy-efficient fire detection systems.

Research is currently underway to explore how an IoT-based fire detection system can be integrated with existing emergency response systems, enabling faster and better coordinated action. The importance of forest fire monitoring stems from the significance of forest resources and the destructive impact of forest fires on climate change. RFID technology is of strategic importance in modernizing fire monitoring in the forestry sector. Two popular approaches are predicting the likelihood of a fire in an area and detecting forest fires in their early stages through associated gas and aerosol emissions and temperature increases. Fires in their early stages are easier to control and mitigate. RFID's ability to tag, track and monitor assets in real time [8] [9] provides forest managers with a powerful tool for optimizing their operations. In [10], a system can be used for forest fire monitoring. This system uses trees from a plot that can be tagged with inexpensive and durable RFID tags that can store data on most tree characteristics. In [11], RFID sensors are used for early detection of forest fires in order to obtain real-time information for monitoring the surrounding area in the event of a fire and generating alerts.

It is crucial to note that the precise location plays a vital role in an area covering several square kilometers of forest. While the base station may detect that a fire has occurred, it is unable to pinpoint its exact location. Satellite images and drones are sometimes used to locate fires, but they are only effective once the fire has reached a certain size and is visible above the trees, by which time significant damage has already been done. They are not useful for early fire detection systems. The approach taken by these techniques is to use sensors whose locations are known, called reference sensors, and to calculate the locations of unknown sensors relative to the reference sensors. Localization techniques fall into two categories: range-based [12] and non-range-based [13]. Range-based techniques [14] use hardware devices to determine the relative positions of unknown nodes with respect to beacon nodes by measuring the distance between them. Factors such as received signal

strength indicator (RSSI) [15], angle of arrival (AoA) [16] and time of arrival (ToA) [17] are used to calculate this distance. Range-free techniques [18] use information such as node identifiers, connection patterns or topological data [19] to estimate the location of the sensor. The techniques proposed to date suffer, to some extent, from localization errors.

Several challenges must be addressed. The implications of climate change and the resulting increase in fire risk require adaptation strategies. Recently, artificial intelligence (AI) has emerged as a promising tool for improving accuracy in IoT design. Despite various technological and management approaches to forest fire prediction and detection, the results obtained remain insufficient. There is therefore a need to improve existing methodologies and develop new ones to better protect forest ecosystems. Among the most recent models is an artificial neural network (ANN) model [20]. A study conducted in [21] investigated the influence of wooded areas, particularly the Amazon rainforest. The localization method is based on the collection of received signal strength indicators (RSSI) combined with artificial neural networks (ANN) to predict signal strength in an Amazonian forest environment. This method can be used for forest fire detection.

Locating sensors is a difficult task, particularly when the sensor network is deployed over a large area (Figure 1). In Figure 1, a network of randomly deployed RFID sensors is used for early detection of forest fires. An ideal forest fire monitoring system should be able to monitor a large area (spatial coverage) with reasonable frequency (temporal coverage).

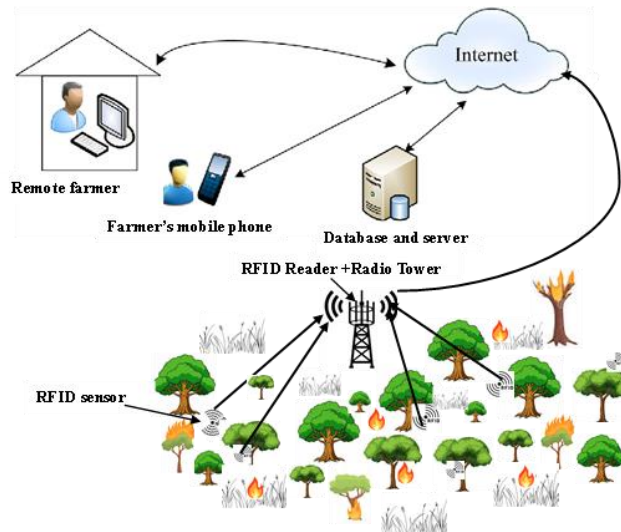


Figure 1. Diagram of the RFID system for forest fire detection

The rest of the article is organized as follows. Section II presents the conventional localization algorithm based on RSSI/AoA hybrid data collection. Section III describes the positioning field concepts and the RSSI/AoA hybrid method based on artificial neural networks (ANN) used in this document. Section IV describes the system model and methods used in this document. Finally, conclusions and prospects for future work are presented in Section IV.

2. Hybrid AoA/RSSI reader localization using 3D multilateration.

In this study, the problem of distributed target location based on RSS and AoA measurements is addressed. Multilateration is a method for predicting position using a hyperbolic algorithm. Multilateration estimates the coordinates of the target node (reader) from the distances between the target node (reader) and n reference nodes (RFID sensors) whose coordinates are known in a forest area of interest. Figure 2 shows how the position of the RFID reader can be estimated using the

Multilateration method, where the distance from the reader to the reference points (RFID sensors) Sensor1 (x_1, y_1, z_1) , Sensor 2 (x_2, y_2, z_2) , Sensor 3 (x_3, y_3, z_3) and Sensor 4 (x_4, y_4, z_4) is estimated respectively with distances d_1, d_2, d_3 and d_4 in the forest area for forest fire detection.

The different powers of the RSS and their different angles of arrival: angle of arrival (AoA) of each sensor antenna.

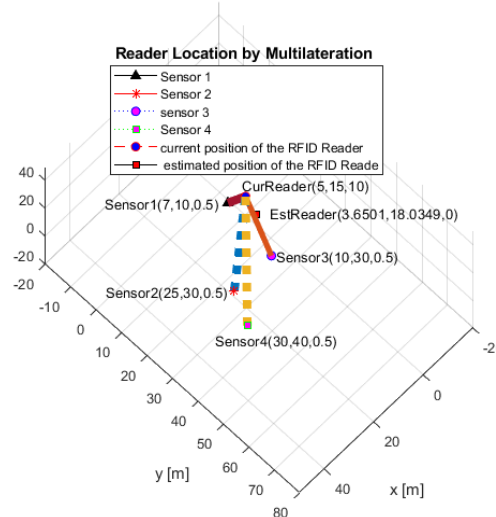
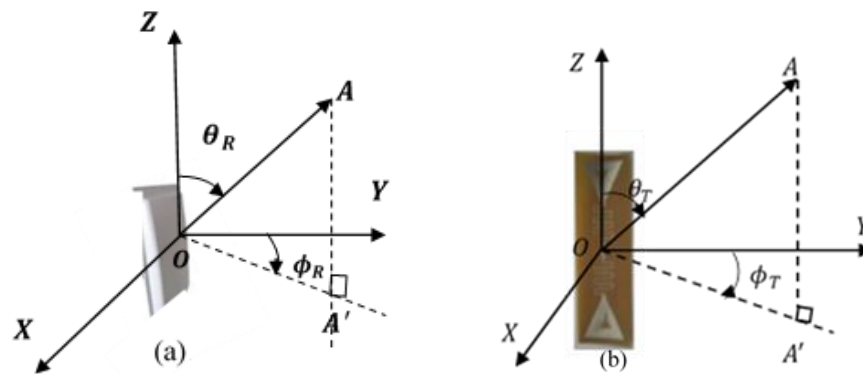


Figure 2: Estimating the position of the RFID reader using multilateration (3D)

Figures 3 and 4 show that the gains of the RFID reader antenna and the RFID sensor antenna have a direct impact on the accuracy of the reader's RSSI. Therefore, obtaining accurate expressions for the gain of the reader antenna and the RFID sensor antenna is crucial for RSSI estimation. Antenna gains depend on the positions of the sensor and reader antennas. In this study, as is the case in forested areas, the reader is mounted on a radio tower at a height above the sensors. In addition, the reader antenna radiates downwards, as shown in Figures 1 and 4.

The angular gains or angles of arrival (AoA) of the patch antenna for the $G_{Reader}(\theta_R, \phi_R)$ and the dipole antenna for the $G_{Sensor}(\theta_T, \phi_T)$ are expressed in the work of [22].



(a) : Reader's antenna with patch

(b) : RFID sensor antenna

Figure 3. Spherical coordinates of the antennas: (a) Reader antenna with square patch; (b) RFID sensor antenna.

The gain of a reader patch antenna as a function of the angle of arrival (AoA) can be expressed as:

$$G_{reader}(\theta_R, \phi_R) = G_R = 3,136 [\tan(\theta_R) * \sin(0,5\pi * \cos(\theta_R)) * \cos(0,5\pi * \sin(\theta_R) * \sin(\phi_R))]^2 \quad (1)$$

The gain of a half-wavelength sensor antenna can be expressed as:

$$G_{sensor}(\theta_T, \phi_T) = G_T = 1,641 * [\cos(0,5\pi \cos(\theta_T))]^2 / (\sin(\theta_T))^2 \quad (2)$$

The spatial relationship between the sensor antenna and the reader antenna is described in the work of [23][23]:

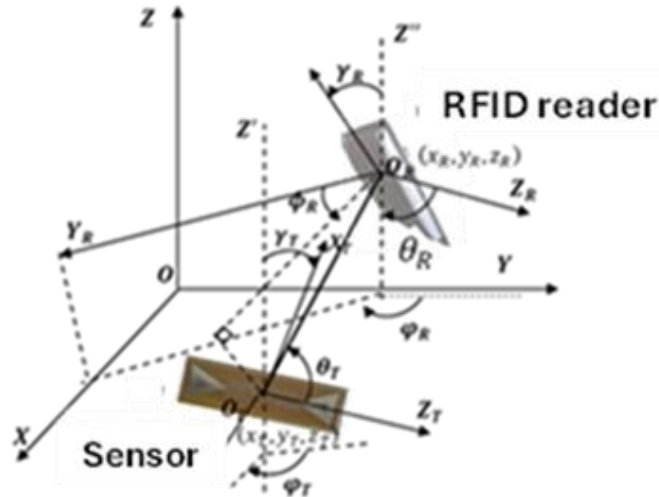


Figure 4: Cartesian coordinate system for characterizing the sensor and reader.

Where:

(x_T, y_T, z_T) : coordinates of the RFID sensor; (x_R, y_R, z_R) : coordinates of the reader.

(γ_R, φ_R) : position of the reader; (γ_T, φ_T) : position of the sensor.

Let θ_T , θ_R , ϕ_R and ϕ_T be the respective sets of true azimuths and elevations describing the angles of arrival (AoA) of a wireless signal for each of the RFID sensors. These pairs of angles can be expressed geometrically as a function of the positions of the corresponding sensors. The gains $G_{sensor}(\theta_T, \phi_T)$ and $G_{reader}(\theta_R, \phi_R)$ are determined by referring to the direct line of sight as the object of analysis. The expressions for the angles of arrival (AoA) θ_R , ϕ_R and θ_T given in the work of [23]:

$$\theta_R = \arccos\left(\frac{x_{R,T} \cos \varphi_R - y_{R,T} \sin \varphi_R}{d}\right) \quad (3)$$

$$\phi_R = 0,5\pi - \left(\arctan\left(\frac{x_{R,T} \sin \varphi_R + y_{R,T} \cos \varphi_R}{z_{R,T}}\right) + \gamma_R\right) \quad (4)$$

$$\theta_T = \arccos\left(\frac{(x_{R,T} \cos \varphi_T - y_{R,T} \sin \varphi_T) \cos \gamma_T + z_{R,T} \sin \gamma_T}{d}\right) \quad (5)$$

With

$$d = \sqrt{x_{R,T}^2 + y_{R,T}^2 + z_{R,T}^2}; x_{R,T} = x_R - x_T, y_{R,T} = y_R - y_T, z_{R,T} = z_R - z_T. \quad (6)$$

By inserting equations (3) and (4) into equation (1), and equation (5) into equation (2), the expressions for $G_T(\theta_T, \phi_T)$ and $G_R(\theta_R, \phi_R)$ can be obtained as functions of $(x_{R,T}, y_{R,T}, z_{R,T}, \gamma_T)$ and $(x_{R,T}, y_{R,T}, z_{R,T}, \varphi_R, \gamma_R)$, respectively.

Various parameters including the distance and RSSI between the reader and the target sensor are then calculated based on the indication of the received signal strength and the angle of arrival (AoA).

Position determination requires both the angle of arrival (AoA) and range. The latter is calculated from the absolute values of RSSI, so this value is more sensitive to RSSI measurement uncertainties.

In (9), the unknown is the reader's position (x, y, z). For N RFID sensors, we obtain N systems of equations (13). Locating the sensors using the multilateration method consists of solving the system of N equations. Next, we formulate the estimation problem and transform it into a linear equation. We formulate the estimation problem using the conventional methods of [24] [25] [26]:

Taking into account the shadowing effect using the log-normal path loss model, the power received by the reader from each RFID sensor is expressed by relation (7):

$$P_i^{reader} = K_i \frac{P_{tx}}{d_i^\alpha S_i}, i=1,2,..., N. \quad (7)$$

where $S_i = 10^{0.1X_i}$ is a log-normal random variable, X_i is a Gaussian random variable with mean zero and variance σ^2 , and the other parameters are the same as in relation (7).

$$K_i = \frac{1}{T_p G_p^2} \left(\frac{\lambda}{4\pi} \right)^4 G_{tag_i}^2 G_{reader_i}^2 \quad (8)$$

With

$T_p = 1/3$: represents the system losses in both the sensor and reader;

$G_p = 0.01$: gain penalty.

To minimize the undesirable effect of shadowing, the RSS values (P_i^{reader} values) as a function of the arrival (AoA) are averaged as shown in relation (9):

$$\frac{K_i}{P_i^{reader}} = \frac{[(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2]^{2/\alpha}}{P_{tx}}, i=1,2,..., N \quad (9)$$

Taking the power $2/\alpha$ on both sides, we obtain:

$$\left(\frac{K_i}{P_i^{reader}} \right)^{2/\alpha} = \frac{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2}{P_{tx}^{2/\alpha}}, i=1,2,..., N. \quad (10)$$

$$\left(\frac{K_i}{P_i^{reader}} \right)^{2/\alpha} = \frac{x^2 + y^2 + z^2 - 2xx_i - 2yy_i - 2zz_i + x_i^2 + y_i^2 + z_i^2}{P_{tx}^{2/\alpha}}, i=1,2,..., N \quad (11)$$

By isolating the term $x_i^2 + y_i^2 + z_i^2$, we obtain:

$$x_i^2 + y_i^2 + z_i^2 = 2xx_i + 2yy_i + 2zz_i + \left(\frac{K_i}{P_i^{reader}} \right)^{2/\alpha} P_{tx}^{2/\alpha} - (x^2 + y^2 + z^2), i=1,2,..., N. \quad (12)$$

Since this last equation is valid for each node, it can be extended to all nodes and expressed in matrix form as follows:

$$\begin{bmatrix} 2x_1 & 2y_1 & 2z_1 & \left(\frac{K_1}{P_1^{reader}} \right)^{2/\alpha} & -1 \\ 2x_2 & 2y_2 & 2z_2 & \left(\frac{K_2}{P_2^{reader}} \right)^{2/\alpha} & -1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 2x_N & 2y_N & 2z_N & \left(\frac{K_N}{P_N^{reader}} \right)^{2/\alpha} & -1 \end{bmatrix} \begin{pmatrix} x \\ y \\ z \\ (P_{tx})^{2/\alpha} \\ x^2 + y^2 + z^2 \end{pmatrix} = \begin{pmatrix} x_1^2 + y_1^2 + z_1^2 \\ x_2^2 + y_2^2 + z_2^2 \\ \vdots \\ x_N^2 + y_N^2 + z_N^2 \end{pmatrix} \quad (13)$$

Finally, the formulation of the estimation problem and its transformation into matrix form:

$$AX = b \quad (14)$$

A simple approach to solving a system of linear equations is to use the LS method. The LS solution to the above system is as follows:

$$\hat{X} = (A^T A)^{-1} A^T b \quad (15)$$

The estimation problem formulated as a matrix can be easily solved using the least squares method to minimize the disturbances caused by the shadowing effect in the measurements. This linear equation can be solved using the least squares method. The solution to relation (14) provides not only the position of the transmitter, but also its EIRP. In particular, the value $(P_{tx})^{2/\alpha}$ is found. Once solved, the quantities x , y , and P_{tx} obtained are called x_{est} , y_{est} , z_{est} , and P_{est} , respectively. A solution for better performance with respect to the mean square error (MSE) can be obtained.

To evaluate the performance of RSSI/AoA-based localization, the mean square error (MSE) for the reader position and the mean absolute power estimation error (PEE) are used. The mean square error (MSE) is defined by the relationship:

$$e_{MSE} = \frac{1}{N_{sim}} \sum_{n=1}^{N_{sim}} \sqrt{(x - x_{est,n})^2 + (y - y_{est,n})^2 + (z - z_{est,n})^2} \quad (16)$$

Where:

(x, y, z) is the true position of the reader; $(x_{est,n}, y_{est,n}, z_{est,n})$ is the n th estimate of the reader's position; N_{sim} is the number of simulations runs.

The mean absolute power estimation error (PEE) is then defined by the following relationship:

$$e_{PEE} = \frac{1}{N_{sim}} \sum_{n=1}^{N_{sim}} |P_{tx} - P_{est,n}| \quad (22)$$

Where:

$P_{tx} = 1W$ is the true EIRP (Effective Isotropic Radiated Power) of the transmitter.

$P_{est,n}$ is the n th estimate of the EIRP.

Location simulation is applied to estimate the position. All results are obtained by running the simulation for 10 iterations and averaging the results. The four RFID sensors are placed within the reader's coverage area, as shown in Figures 1 and 2. The RFID sensors are placed on the trees at the same height and therefore have fixed positions. The four RFID sensors are placed in the following positions: RFID sensor 1 (7m, 10m, 0.5m); RFID sensor 2 (25m, 30m, 0.5m); RFID sensor 3 (10m, 30m, 0.5m); RFID sensor 4 (30m, 40m, 0.5m) and the reader mounted on occupies the position (5m, 15m, 10m) to identify the RFID sensors in its coverage area.

It is assumed that the parameter K_i representing the factors affecting the RSS+AoA values at the j -th sensor are a function of the sensor positions and the different gains, that the path loss exponent α is equal to 3, and that the sensor positions are those indicated in. It is also assumed that the EIRP of the RFID reader is 1W.

Figures 5 and 6 show the plots of the MSE and PEE position estimates as a function of the number of iterations. In this model, X_i (X_{Gi}) is a random variable with a standard deviation σ , which affects the RSSI value and thus influences the estimated mean localization error. As shown in Figures 5 and 6, the simulation is performed with four (4) RFID sensors deployed with different standard deviations (σ) to study the estimated average location error. The number of sensors and readers in these simulations is fixed. The convergence of the hybrid RSSI/AoA method in terms of the number of iterations is evaluated.



Figure 5: Mean square error as a function of the number of iterations for standard deviations $\sigma=3\text{dB}$ and $\sigma=6\text{dB}$



Figure 6: Absolute power estimation error as a function of the number of iterations for shadowing standard deviations $\sigma=3\text{dB}$ and $\sigma=6\text{dB}$.

According to Figure 5, tracking errors in terms of MSE can be significantly reduced after 3 iterations. The MSE of the estimated position decreases as the number of iterations increases. Performance is further improved and stabilized with 10 iterations. The simulation results of the hybrid RSSI/AoA method for the estimated MSE after 10 iterations are respectively $\text{MSE}=3.57455\text{m}$ for $\sigma=3\text{dB}$, $\text{MSE}=3.577456\text{m}$ for $\sigma=6\text{dB}$. Furthermore, even though the standard deviations of the hybrid method are different, the convergence behavior is very similar.

Figure 6 shows the effects of the number of iterations on the mean power estimation error for different values of the standard deviation σ where $\sigma=3\text{dB}$ and $\sigma=6\text{dB}$ (i.e. measurements with noise). In particular, the mean absolute power estimation error decreases as the number of iterations increases. The simulation results of the hybrid RSSI/AoA method for the estimated power after 10 iterations are respectively $\text{PEE}=0.900279\text{W}$ for $\sigma=3\text{dB}$ and $\text{PEE}=0.90029\text{W}$ for $\sigma=6\text{dB}$.

3. Localization using the RSSI/AoA hybrid based on ANN

RSSI/AoA hybrid-based localization has certain drawbacks, such as the risk of errors caused by environmental factors such as dirt, extreme temperatures, the enormous volume of data that is difficult to manage, and the need for longer read ranges due to the reduction in signal strength caused by propagation through vegetation cover. However, improvements in machine learning and statistical modelling methods are helping to increase the accuracy of RFID systems.

Finding an algorithm that avoids all these problems is not easy and requires considerable resources in all cases. That is why this article proposes the use of artificial neural networks as an approach to systematically solve the problem of detection errors and fire location. ANNs not only have the ability to process noisy RSSI+AoA measurements, but they also have the ability to learn and be trained quickly. However, the choice of ANN type for the application of forest fire prevention to combat global warming has to be appropriate. The input to the proposed ANN architecture consists of the RSSI/AoA measurements received from the four RFID sensors, i.e. RSSI+AoA (1), RSSI +AoA (2), RSSI AoA (3) and RSSI+AoA (4), while the x, y and z coordinates of the target (RFID reader) constitute the output using the Hopfield neural network as illustrated in Figure 7. The implementation of the Hopfield network is called a generalized linear neural network (GLNN) [27]. The generalized linear neural network (GLNN) is an extension of the Hopfield neural network that uses linear activation functions.

In the literature, conventional continuous-time gradient-based Hopfield neural networks [28] [29] have been developed and extensively studied for solving linear systems (27).

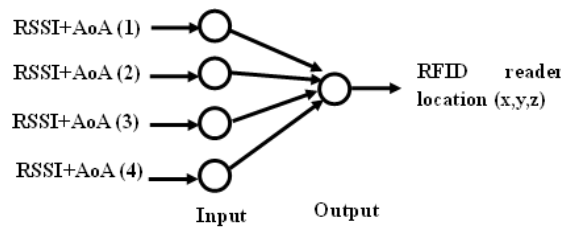


Figure 7: HNN architecture for reader (target) localization

The design procedure is summarised as follows. The normalised scalar quadratic minimisation error function is defined using Equation 23:

$$MSE = \frac{1}{2} \|Ax - b\|_2^2 \quad (23)$$

Where $A \in \mathbb{R}^{m \times n}$ with $m < n$ is the rectangular real matrix of the model; $b \in \mathbb{R}^{1 \times m}$ is the vector of observations or measurements; and $X = [x, y, z]^T$ is the unknown vector of system parameters to be estimated for the position of the RFID reader in the forest coverage area. Thus, the weight update formulas and the update vector for the HNN model shown in Figure 7 are given by equations (24) and (25), respectively:

$$w(k+1) = w(k) - \eta A^T (Aw(k) - b) \quad (24)$$

And

$$x_{k+1} = (b - \eta A^T A) x_k + A^T b \quad (25)$$

With $\eta > 0$: the learning rate of the network, $\eta = \frac{1}{2 \cdot \text{trace}(A \cdot A^T)}$.

The coefficients A and b used in the hybrid RSSI/AoA approach, as well as a weight update matrix given by equation 24, are generated in the simulations during the RNA tests. The path loss assumptions are those of equation 8, and the path attenuation exponent $\alpha=3$ for all simulations. The noise model is given by the random variable $X_i(X_{\text{oi}})$ with standard deviations $\sigma=3\text{dB}$ and $\sigma=3\text{dB}$ for all simulations.

The four RFID sensors are placed within the reader's coverage area, as shown in Figures 1 and 2. The RFID sensors are placed on the trees at the same height and therefore have fixed positions. The four RFID sensors are placed in the following positions: RFID sensor 1 (7m, 10m, 0.5m); RFID sensor 2 (25m, 30m, 0.5m); RFID sensor 3 (10m, 30m, 0.5m); RFID sensor 4 (30m, 40m, 0.5m) and the reader mounted on occupies the position (5m, 15m, 10m) to identify the RFID sensors in its coverage area.

The position of the reader varies randomly, and each time the identification of the RFID sensors by the reader is estimated using equation (15). In this hybrid approach, the Hopfield-type neural network is used to estimate the position and correct it. RSSI + AoA + HNN-based localisation is implemented by solving equation (14). A localisation simulation is applied to estimate the position and EIRP of the RFID reader. All results are obtained by running the simulation 10 iterations and averaging the results. As indicated in Section 2, we assume that the parameter K_i representing the factors affecting the RSSI+ AoA+HNN values at the j -th sensor are a function of the sensor positions and different gains, that the path loss exponent α is equal to 3, and that the sensor positions are those indicated in. We also assume that the EIRP of the RFID reader is 1W.

Figure 8 shows the convergence of neural weights. It can be seen in Figure 9 that most weights converge to relatively larger values, while only partial weights remain in the vicinity of zero. Based on Figure 8, it can be concluded that not only the HNN weights converge towards their ideal values, but also that the convergent weights may well approach the non-linear function for the location of the RFID reader.

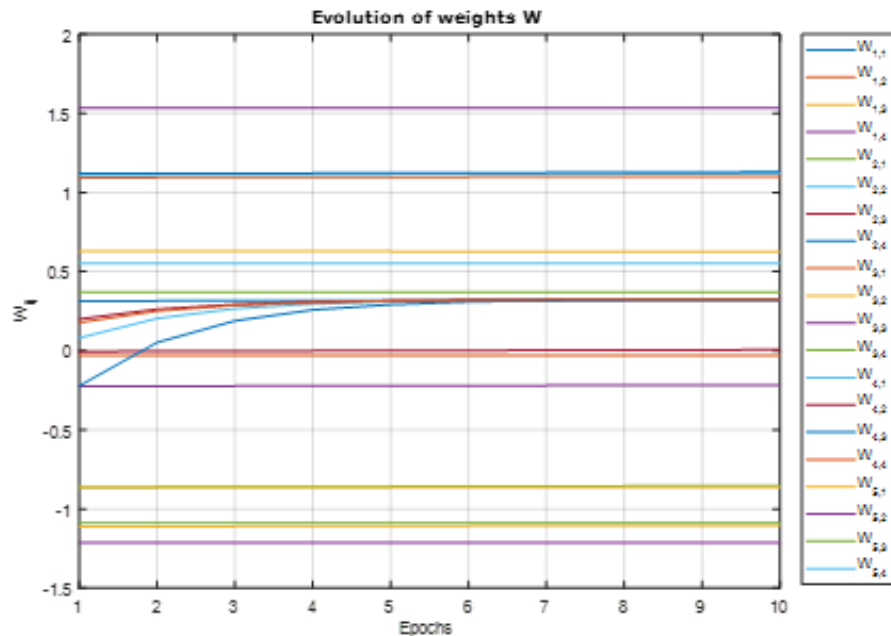


Figure. 8. Convergence of the RSSI+ AoA+HNN weights.

Figure 9 shows the curve MSE plotted as a function of the number of iterations for the Hopfield type neural network. It is observed that the mean square error for the estimated values of the location of the RFID reader decreases with the number of iterations, which confirms the effectiveness of the Hopfield-type neural network in finding the optimal solution.

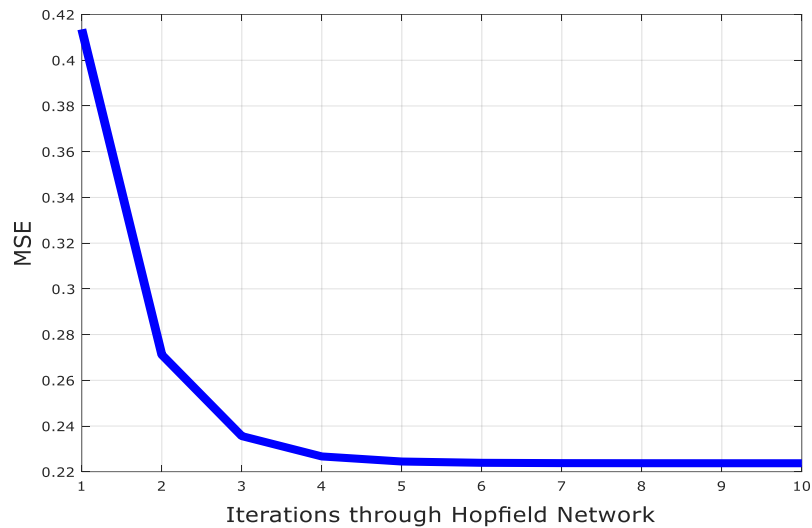


Figure 9. Root mean square error for the estimated reader position via the Hopfield network

Figure 10 compares the mean square errors (MSE) as a function of the number of iterations of the hybrid RSS/AoA method and the RSSI+ AoA+HNN method, respectively.



Figure 10: Comparison of overall performance between RSS/AoA and RSSI+ AoA+HNN based on the number of iterations for standard deviations $\sigma=3\text{dB}$ and $\sigma=6\text{dB}$

Figure 10 compares the mean square error (MSE) of the RSS/AoA hybrid and the proposed RSS+AoA+HNN positioning algorithm. For the tenth iteration, we obtain an MSE of 3.5755m and 3.57456m, respectively, for the respective standard deviations $\sigma=3\text{dB}$ and $\sigma=6\text{dB}$ for the RSS +AoA algorithm, while RSS+AoA+HNN obtains a much lower MSE of 0.2208m for all standard deviations. This indicates that the proposed RSS+AoA+HNN algorithm achieves a lower estimation error and therefore offers greater accuracy than RSS+AoA. The use of distance and angle measurements combined with the artificial neural network allows for more accurate localization of forest fires in order to combat global warming.

4. Conclusion

In this article, an artificial system was proposed to detect and correct the RSSI+AoA values of RFID sensors used to locate forest fires in order to combat global warming. This model, based on an artificial neural network, enables the prediction of forest fires and was developed for the first time. The results showed a significant improvement in range and position accuracy compared to the hybrid RSSI+AoA method. It was observed that the proposed method improves localization solutions in complex forest environments by taking into account path loss and the shadowing effect. Thus, the proposed model, RSSI+AoA+HNN, achieved better accuracy, with MSE values of 0.2208m with standard deviations of 3dB and 6dB, respectively, to improve the RSSI+AoA hybrid influenced by environmental parameters.

For future work, several improvements could be made to the current work. First, the proposed system should be trained and tested in increasingly complex dynamic areas and scenarios. Secondly, the system should be tested in real-world environments that are more complex than those tested in this article, with real traffic and multiple obstacles. Training the ANN to identify multiple human obstacles is one of the most important areas of research, along with other AI algorithms.

Conflict of Interest

We declare no conflict regarding the publication of the study.

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