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Real-Time Data Estimation Algorithm Using E-training and Wireless Sensor Network

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Abstract
Natural disasters, such as forest fires, pose a significant threat to the environment and living organisms, jeopardizing plant and animal species. In addition to their direct contribution to air pollution and climate change, Wireless Sensor Networks (WSNs) have garnered the attention of researchers and developers for various contemporary applications, including environmental surveillance and monitoring forest fires. Fast and accurate estimation of when some natural disasters, such as fires, reach specific areas despite the random distribution of sensors in a very large area is considered a serious problem due to the range of detection and coverage- related problems. This paper presents a framework for a wireless sensor network simulation that enables real-time detection and monitoring of forest fires through the use of flame. The proposed model is designed using the MATLAB program, e-training, and its aim is to achieve three main goals: to address forest fires more efficiently than traditional approaches by accurately predicting the dynamics of fire propagation; examine the relationship between the spatial density of randomly positioned sensor nodes within the region and the precision of fire spread predictions. The third and final goal is to establish the best path for the firefighting vehicle that ensures the fire is surrounded at the least possible time.

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Keywords: Wireless Sensor Network (WSN), E-training, MATLAB, Sensor nodes, Firefighting

Introduction

The ecological stability of the Earth's environment heavily depends on its forests. Unfortunately, wildfires are of- ten only detected after they have already extensively spread throughout an area, rendering their organization and control extremely challenging, if not outright impossible, at times. This leads to substantial and long-lasting harm to the ecosystem and the atmosphere, as wildfires contribute significantly to atmospheric carbon dioxide levels (30% of atmospheric carbon dioxide (CO2) is a contribution from wildfires) [1]. Other long-term negative repercussions of forest fires include implications for global warming, the extinction of plants and animals, and regional weather patterns [2]. Additionally, significant financial losses under-score the critical need for an effective, simple, and cost-efficient approach to monitoring and preventing forest fires. Today, the wireless sensor network stands out as one of the most essential and effective technologies for managing this challenge.

Wireless sensor networks have recently emerged as one of the most essential technologies, finding application in a wide range of critical domains [3]. A wireless sensor network consists of randomly deployed sensor nodes that aim to sense and collect physical data within their sensing range. These sensor nodes can autonomously reorganize the network to maintain connectivity when any node within the WSN fails. The specific values sensed depend on the wireless sensor network's application, which could include wind speed, temperature, humidity, pressure, light intensity, and others. The data may be transmitted on a regular schedule or in response to specific events [4]. The base station or sink serves as an interface, connecting the wireless sensor network to end users who access the network through a local area network or the broader reach of the Internet [5]. The general architecture of a WSN illustrated in Figure (1) depicts the sensor nodes randomly distributed in a sensing field or sink positioned at the end of it.

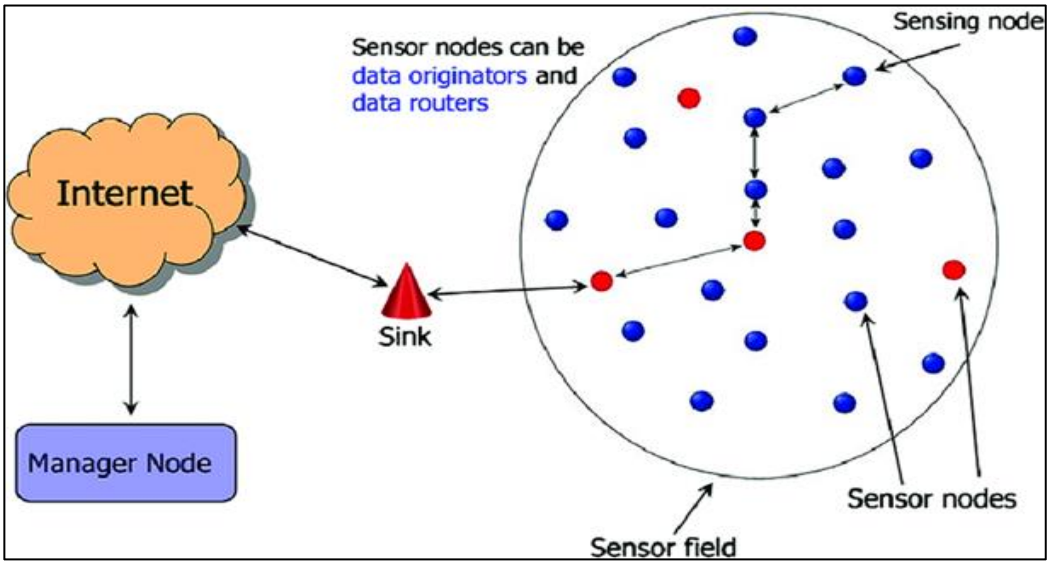

Fig 1: Wireless Sensor Network (WSN) General Architecture

Sensor nodes can be deployed in random or pre-planned distributions. Randomly deploying a large number of nodes in expansive, unobstructed outdoor areas like forests can facilitate monitoring and reporting tasks. However, this approach poses challenges related to coverage and network maintenance, such as managing connections, data collection, and issue identification due to the high node density. Alternatively, a pre-planned deployment with fewer nodes in specific regions can be more suitable for limited indoor coverage, offering the advantage of lower network maintenance and management costs [7]. The simplicity of setup and configuration, affordability, and energy-efficient design, coupled with the ubiquity of wire- less sensor networks in contemporary applications, have catalyzed the rapid advancement of related technologies, including standardization and cost-effective, user-friendly implementation approaches [8]. The difficulties are related to the operation of the WSN in extreme atmospheric conditions [9], limited energy, and quality of service (QoS), the extent to which the gathered data can be understood and utilized by the receiver. Additionally, security, privacy, and adaptability are crucial considerations (The architecture of a wireless sensor network must be sufficiently sophisticated and resilient to handle a wide range of applications and dynamic topological conditions) [10]. Pan, Ligong in 2020 [11]: Proposed a framework for a dynamic wireless network of reflecting sensors that can monitor on-site meteorological conditions and adaptively reconfigure the network to ensure effective coverage area. Sungheetha, Akey, and Rajesh Sharma in 2020 [12]: A proposed fire detection system leverages wireless sensor networks (WSNs) to identify fire events and the Internet of Things (IoT) for ongoing monitoring. For further validation of the incident, the system is enhanced by drone technology and image processing. This solution is reliable, boasting a detection accuracy of up to 98%, but it comes at a high cost. Dasari, Premsai, *et al*. in 2020 [13]: An automated forest fire detection and alert system has been proposed, utilizing fire and smoke sensors that communicate via radio frequency. This system is designed to promptly notify end-users or government authorities of any detected fires, employing a global system for mobile communication to transmit SMS alerts. Silva, I. D. B., Valle, M. E., Barros, *et al*. In 2020 [14], a proposed wildfire early warning model is obtained by aggregating two indexes: wildfire risk (the forest's georeferenced features) and wildfire danger (the weather's instantaneous conditions). These two indices are determined using machine learning techniques and fuzzy logic operations. Jain, Khushboo, *et al.*, in 2021 [15]: The paper presents a novel predictive approach re- lying on data correlation to eliminate redundant data within the sensor network; an advanced linear regression technique was applied in the predictive model. Alkhatib, Ahmad AA, *et al.* in 2021 [16]: "Developed a subnetwork cover- age method to convert networks with a random distribution of sensors into an organized deployment."

Numerous recent studies have utilized extrapolation and curve-fitting techniques to predict data beyond the defined limits of a function's domain. Extrapolation typically involves formulas that leverage information about the function's behavior at specific data points within its domain. When extrapolating from the full domain, this is known as polynomial extrapolation. Conversely, spline extrapolation considers only a portion of the data points. Several studies will be presented that employ extrapolation as a solution to forecasting challenges. Strelkovskaya, I., Solovskaya, I., & Makoganiuk, A. in 2019 [17]: have leveraged wavelet extrapolation techniques, specifically the heat wavelet, as well as various spline extrapolation methods, including linear, cubic, and B-cubic spline functions, to forecast the characteristics of self-similar traffic patterns in IoT networks for objects exhibiting multiple pulsations. Strelkovskaya, Irina *et al*. in 2019 [18]: The researchers developed a spline extrapolation technique using various functional forms (linear, cubic, and cubic B lines) to forecast similar network traffic patterns for both short-term and long-term projections beyond the time period in which the packet data transmission occurred in fifth-generation (5G) mobile networks. Maryati, A., Pandiangan, N., and Purwani, S. in 2021 [19]: proposed an algorithm that compared the performance of Newton's method and the cubic spline interpolation technique in interpolating and extrapolating data related to the hydrogen and iodine gas content during the acid iodide reaction.

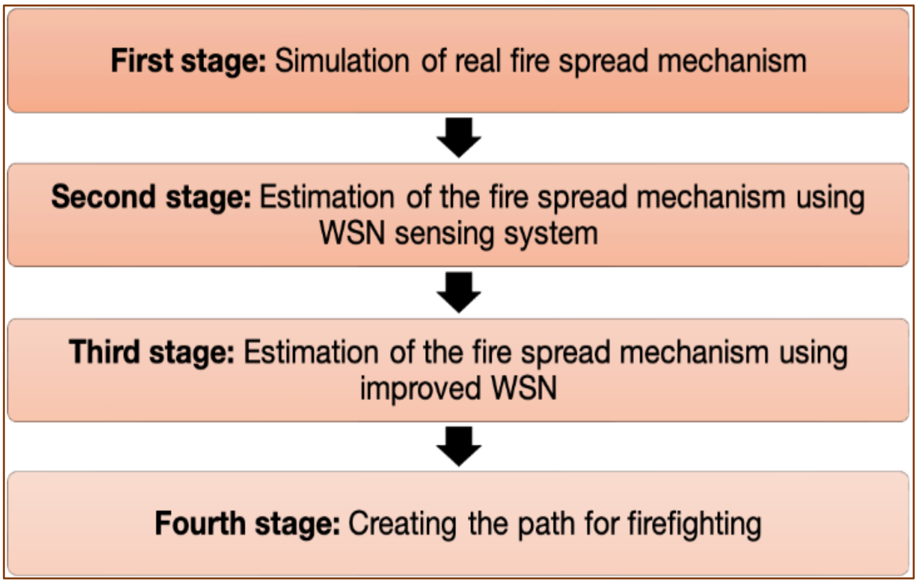

Fig 2: Block diagram of the work stages of real-time data estimation algorithm using WSN

Research Outline

This paper is structured into five principal sections. The first section is an introduction. Section Two provides the theoretical and mathematical foundations underpinning the proposed algorithm. The algorithm is then presented in Section Three. The results obtained through the analysis are discussed in Section Four. Finally, Section Five concludes the work and outlines potential avenues for future research. The paper is supplemented by a list of referenced sources.

Theory

- ***Linear extrapolation:*** Extrapolation based on linear models should be used cautiously, as it may yield inaccurate results when extending beyond the range of observed data points. Linear extrapolation is most appropriate when applied to the points of a linear function graph or when the extrapolation is performed on data points that are close to the known observations. Due to [20], if the two available data points $(x_{i-1}.y_{i-1})$ and $(x_i.y_i)$ are nearest to the extrapolated point $(x.y)$ linear extrapolation is illustrated by the Function (1)

$$y = y_{i-1} + \frac{x-x_{i-1}}{y_i-y_{i-1}}(y_i - y_{i-1}) \qquad (1)$$

Polynomial extrapolation, the general form of linear extrapolation, involves deriving new data points from multiple existing data points. The high-degree polynomial interpolation is demonstrated in Equation (2).

$$f_n(x) = b_0 + b_1(x - x_0) + b_2(x - x_0)(x - x_1) + \cdots + b_n(x - x_0) \ldots (x - x_{n-1})(x - x_n) \qquad (2)$$

Where:

$$f_n(x) = f_i\,(x) = y_i.i = 0.\ldots.n$$

$$b_0 = f(x_0)$$

$$b_1 = f[x_1.x_0] = \frac{f(x_1)-f(x_0)}{x_1-x_0}$$

$$b_n = f[x_n.x_{n-1}.\ldots.x_1.x_0] = \frac{f[x_n.x_{n-1}]-f[x_{n-1}.x_{n-2}]-\cdots-f[x_1.x_0]}{x_n-x_0}$$

The polynomial extrapolation equation is a high-degree function which is the first derivative (slop) of Equation (2) at the end point.

- ***Spline extrapolation:*** Interpolation is the process of estimating values within the range of a set of known data points. Spline functions are a common interpolation technique used to estimate missing or unmeasured data points based on the surrounding observations (for example, linear, cubic, etc.).

Cubic spline interpolation is a method that uses a series of third-degree polynomial segments to model a set of data points within a specific grid cite. Each cubic spline segment requires four data points and ensures continuity at the endpoints. This piecewise approach enables linear interpolation between adjacent grid points. Cubic splines are advantageous when working with multiple data points, as they can avoid the oscillation issues associated with high-degree polynomial interpolation (the range phenomenon).

Spline extrapolation is a method that involves forecasting data outside the available data points using spline functions. Spline functions are mathematical models that can be used to estimate values beyond the observed range [18]. Consider that the available data point is $(x_i.y_i)$ in the available data grid [a; b], $a = x_0 < x_1 < \cdots < x_n = b$. The first-degree spline $S_1(x)$ is a continuous piecewise linear function. let the $yi = f(x_i)$ which describes a function $f(x)$, defined on the interval [a; b]. The interpolation spline is defined by the following conditions:

$$S_1(x_i) = f_i.i = 0.\ldots.n \qquad (3)$$

Geometrically, a spline is a split line passing through the available points of data $(x_i.y_i)$, where $y_i = f(x_i)$. For $x \in [x_i.x_{i+1}].h_i = x_{i+1} - x_i.where\ i = 0.\ldots.n-1$ linear spline equation is:

$$S_1(x) = f_i + \frac{x - x_i}{hi}(f_{i+1} - f_i) \qquad (4)$$

According to [21], the equation of cubic spline interpolation $S_3(x)$ is the same as that of linear spline, except that this will have a cubic function on each pair of $[x_i.x_{i+1}]$,where $i = 1.\dots.n-1$. The cubic spline equation is:

$$S_3(x) = f_i\,(1-t) + f_{i+1}\,t - \frac{h_i^{\,2}}{6}\,t\,(1-t)[(2-t)D_i + (1+t)D_{i+1}]. \quad (5)$$

For $x \in [x_i.x_{i+1}]$, $i = 0.\dots.n-1$.

Where$t = \frac{x-x_i}{h_i}$.

Now if $x > x_n$, a cubic spline extrapolation equation $S(x_e)$ is formed by taking the slop equation of $S_3(x)$ and considering the end point to be the contact point to extrapolate a point of data located outside the grid [a, b]. The cubic spline extrapolation is:

$$S(x_e) = \frac{d(S_3(x))}{dx} \text{ at the end point } (x_3.y_3) \quad (6)$$

Which describes a function $f(x)$, be defined in the interval $[a.b]$. The interpolation spline is defined by the following condition:

$$S_1(x) = fi.i = 0.\dots.n \quad (7)$$

Real-Time Data Estimation Algorithm Using Wireless Sensor Network

1. First work stage: Simulating a real-fire spread mechanism using the influencing factors

Forest fires are a complex and dynamic phenomenon influenced by numerous factors. To accurately simulate the propagation of fires through forests, it is essential to determine the pertinent factors affecting fire spread and understand their respective impacts. In general, the two most salient factors that directly influence the spread of fires can be identified, as shown in Figure (3), which are meteorological variables and fuel. Meteorological parameters encompass measures of wind speed and direction, temperature, and relative humidity. Combustible forest materials, including diverse trees, shrubs, weeds, debris, and decaying vegetation, comprise the fuel load.

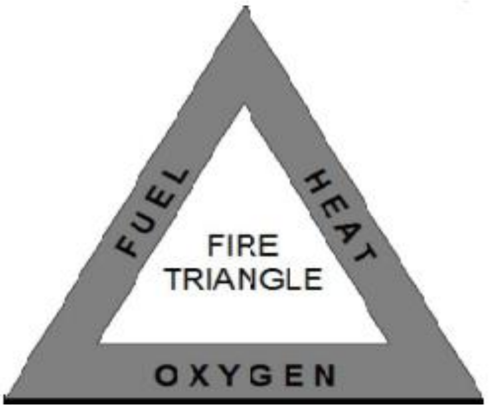

Fig 3: The triangle of fire factors

To simulate fire spread model that changes time and space that explained in Figure (4). This research has derived the following system of equations:

$$\hat{x} = x + \gamma\sigma\varphi[s_e \cos\theta + Bs_w \cos\phi] \quad (8)$$

$$\hat{y} = y + \gamma\sigma\varphi[s_e \sin\theta + Bs_w \sin\phi] \quad (9)$$

5- So, real fire speed is calculated by Equations (3 and 4).

$$Fire\ speed(x) = \frac{\gamma\,\sigma\varphi\,[s_e \cos\theta + Bs_w \cos\phi]}{\text{iterations period}} \quad (10)$$

$$Fire\ speed(y) = \frac{\gamma\,\sigma\varphi\,[s_e \sin\theta + Bs_w \sin\phi]}{iterations\ \text{period}} \quad (11)$$

Where: $\hat{x}$ and $\hat{y}$ represent the coordinates of the next new point, while x and y are the coordinates of the previous point. s_e: Fire speed based on environment flammable material factor. θ : Fire related angle based on start point. B : Wind effect factor. s_w: Wind speed., ϕ : Wind direction angle. φ : Any other random variable that may affect the spread of fire. γ: The humidity effect factor. σ: The temperature effect factor,γ: is a damping factor that has an adverse effect on the spread of fire and its movement from point to point. Calculated in Equation (12).

$$\gamma = \frac{100 - humidity\ number}{100}\ ;\ \gamma < 1 \quad (12)$$

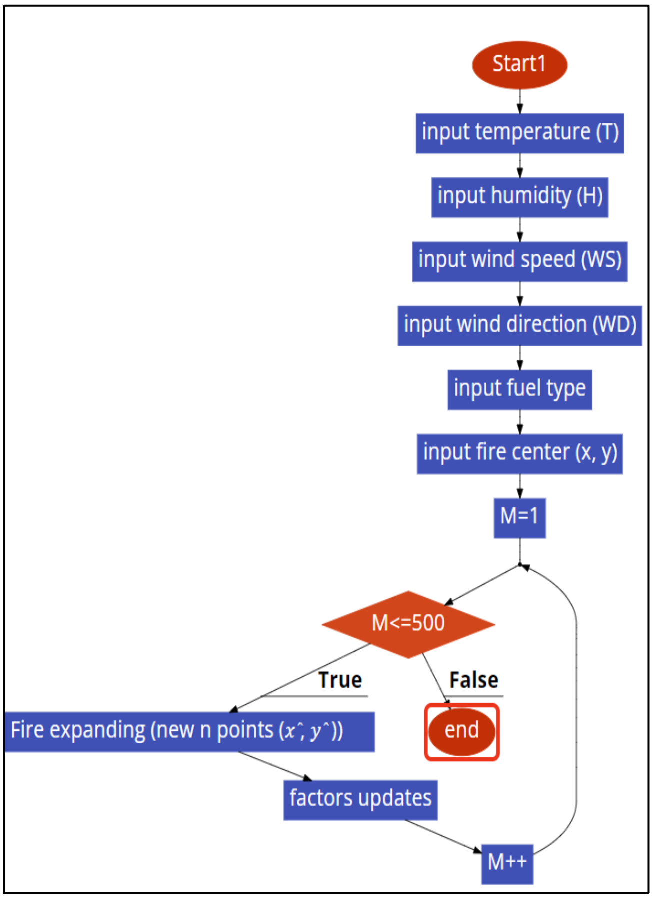

Fig 4: Flow chart of the algorithm's first stage

σ : is an improving factor that has a positive effect on the fire spread and its movement from point to point. Calculated in Equation (13).

$$\sigma = 1 + \left(\frac{temprature\ digree}{100}\right)\ ;\ \sigma > 1 \quad (13)$$

2. Second work stage: Fire detection and fire spread prediction based on the WSN algorithm

Accurate information from existing systems for monitoring forest fires is a significant challenge due to the complexities of the forest's geographical composition and expansive nature. When establishing a wireless sensor network for fire management in forests, a random distribution of sensor nodes is required. However, this randomness introduces several issues, such as computational complexity in data collection from nodes, coverage gaps, and the potential loss of some nodes during deployment.

At this stage, a wireless sensor network-based algorithm has been developed that can effectively address the random sensor distribution issue. By employing extrapolation and curve fitting techniques, the algorithm provides accurate data on forest fires, which enables forecasting of fire spread and predicting the expected time for the fire to reach critical areas. This information empowers firefighters to contain the blaze in a timely manner. A wireless sensor network algorithm has been simulated by the procedure shown in Figure (5).

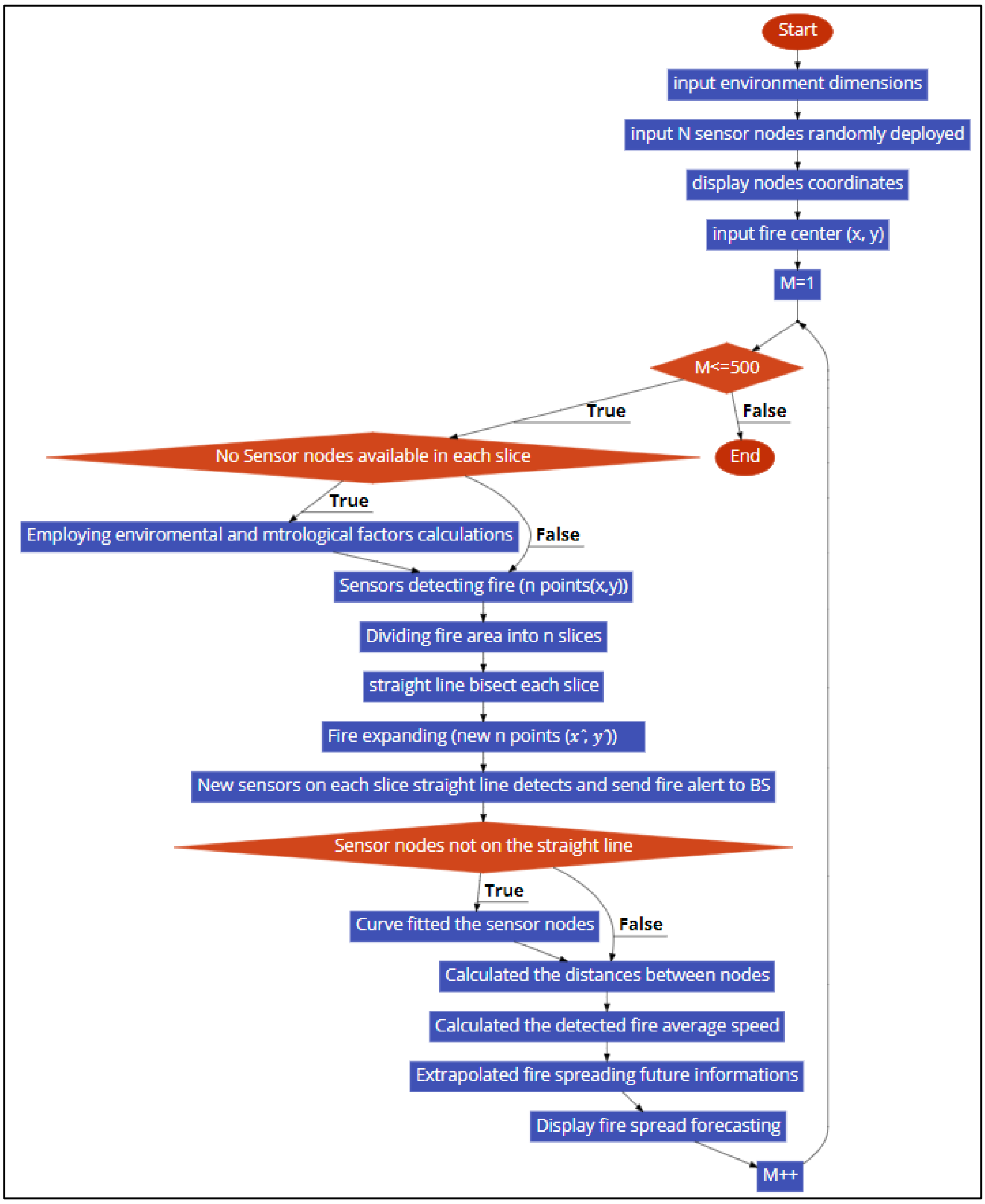

Fig 5: Flow chart of the algorithm's second stage

The fixed sensor nodes, with a specified number (N), were randomly dispersed throughout the designated forest or environmental area during the first stage of the work. These nodes employ GPS-based localization, enabling the algorithm to accurately pinpoint the fire's origin. Once deployed in the region, the coordinates of the node locations are displayed at the base station. The nodes are equipped solely with flame sensors and are programmed to activate an alarm message upon reaching a predefined threshold. This alarm is then transmitted to the sink node. The positioning of the nodes and their alert messages contribute to the overall risk assessment. Additionally, the size, direction, and speed of the fire can be determined by measuring the distances between the nodes that have triggered the alarm.

The fire spread rate has been estimated by calculating the average velocity of fire propagation at each angle and for any cross-section using the Equation. (14) below. Therefore, this equation can be used to estimate the time it takes for the fire to reach any point in the region.

$$S_s = \frac{\sum_{i=1}^{k} \frac{\sqrt{(y_{i+1}-y_i)^2+(x_{i+1}-x_i)^2}}{t_{i+1}-t_i}}{k} \qquad (14)$$

Where: S_s: Fire average speed by sensing system. k: is the number of sensor nodes in each slice around fire area. x, y: coordinates of any point in the slice. t: the time the fire gets to a specific point.

3. Third work stage: Improving WSN sensing system

The precision that has been obtained from the improved system was developed by making use of the affection of the mentioned environmental and metrological factors in the fire spread behavior mentioned in Equations (3- 4) and employing it in the calculations of the WSN sensing system mentioned in Equation (14). Figure (6) illustrated the steps to improve the prediction of fire spread.

The improved WSN system uses the same equations (12 and 13) as used in the second work stage detection system to calculate the error area and the accuracy of the prediction.

$$A_{error} = A_{rf} - A_{pf} \qquad (15)$$

$$P_{Acuracy} = \left[\left(A_{rf} - |A_{error}|\right)/A_{rf}\right] \times 100\% \qquad (16)$$

Where:

$P_{Acuracy}$: The prediction accuracy of WSN.

A_{error} : The error area.

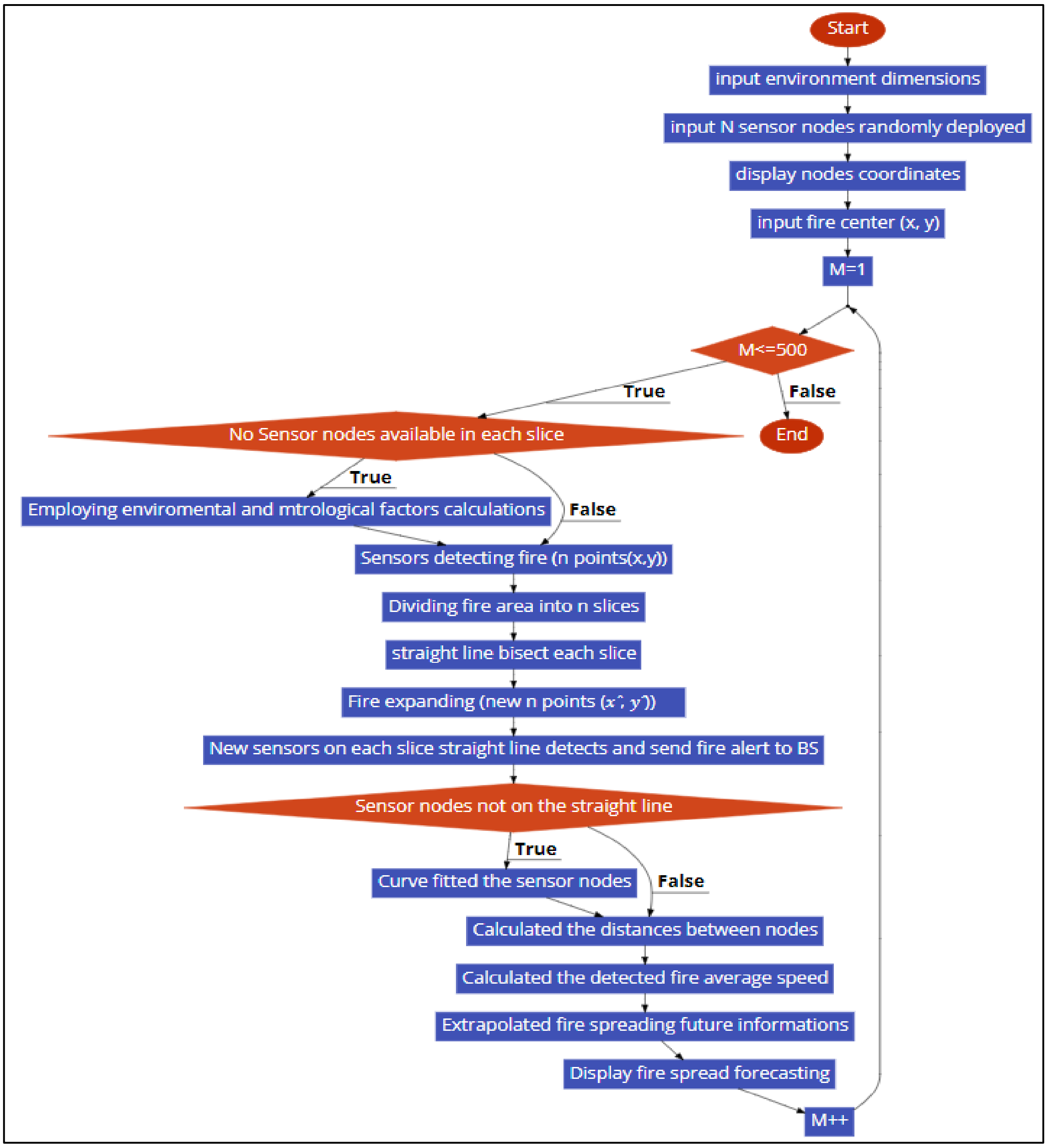

Fig 6: Flow chart of the algorithm's third stage

$A_{rf}.A_{pf}$: The real fire area and the predicted fire area respectively.

The improvement rate ($R_{imP.}$) by which the improved WSN system overcomes the detection system is 6.6% and has been calculated using Equation (17).

$$R_{imp.} = \frac{\sum_{i=1}^{c}(A_{imp.} - A_{sen.})}{c} \qquad (17)$$

Where: $R_{imp.}$: The rate of improvement. $A_{sen.}$: The accuracy of the WSN sensing only system. $A_{imp.}$: The accuracy of the

improved WSN. C: Number of cases.
Table (1) below shows the relationship between the accuracy of the two WSN systems and the initial number of sensor nodes randomly deployed in the area. It is clear that the accuracy has been greatly improved in the improved WSN system.

Table 1: The relationship between the number of sensor nodes and the prediction accuracy of the wireless sensor network system is explored in two scenarios

Number of cases of nodes deployment (c)	**Number of nodes (no. nodes)**	**Average no. of nodes per km^2**	**Accuracy of WSN Prediction**	
			By sensing only ($A_{sen.}$)	By improved sensing ($A_{opt.}$)
1	100	25	56%	83.2 %
2	200	50	75%	89 %
3	300	75	84%	90.4 %
4	400	100	88%	91.2 %
5	500	125	89.7%	92.6 %
6	600	150	90.3%	93 %
7	700	175	92%	93.7 %
8	800	200	92.3%	94.5 %
9	900	225	92.7%	95.3%
10	1000	250	93%	96.1 %

3.4 Fourth work stage: creates the best path for the firefighting truck to surround the fire

In the final stage of the algorithm, a path was generated for the firefighting vehicle to follow in order to encircle the fire and ensure complete extinguish. Due to the unpredictable nature of the fire's behavior, this path is irregular. If the path were to be approximated as a circular shape, it would have a specific radius. The optimal radius R of this path is determined through an iterative trial-and-error process utilizing the bisection method. The radius discovered must satisfy the condition specified in Equation (18), this approach ensures the fire is fully contained within a defined perimeter, while also maintaining a sufficient safety buffer between the fire and the firefighting equipment to prevent unnecessary resource expenditure. Figure (7) shows the path parameters. The steps by which this stage has been formulated are illustrated in Figure (8).

$$T_{vehicle} < T_{fire} \tag{18}$$

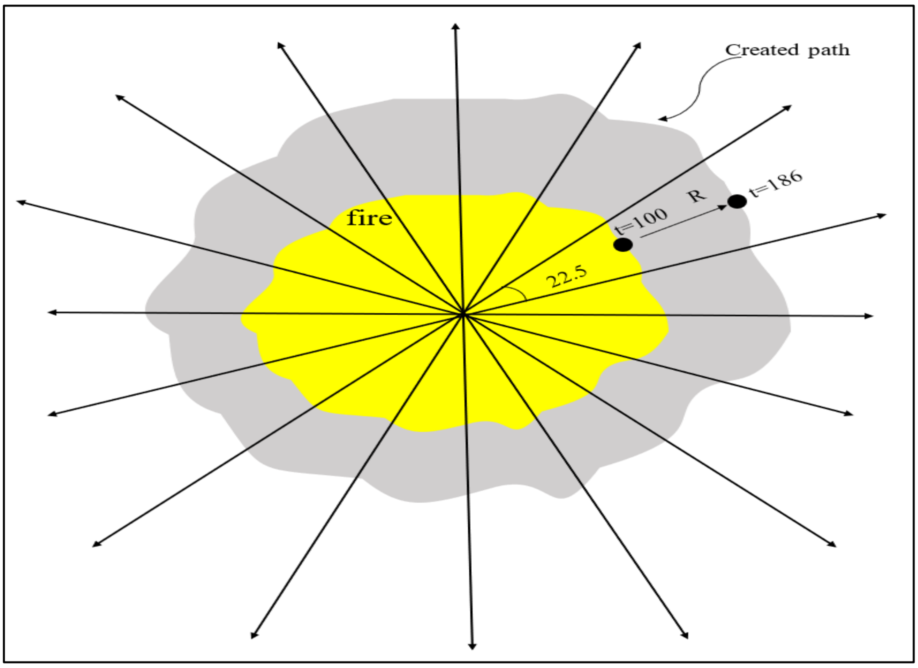

Fig 7: Firefighting path surrounds the fire

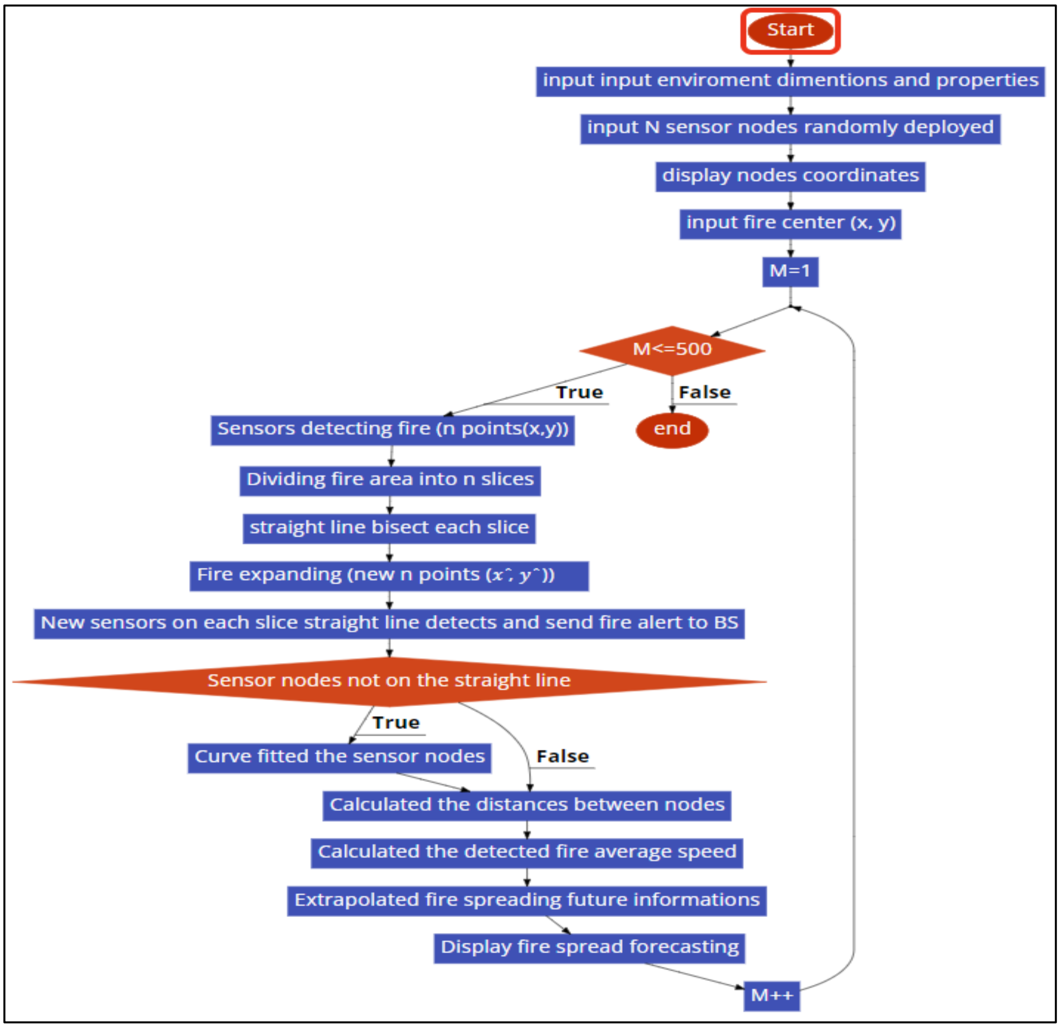

Fig 7: Flow chart of the algorithm's fourth stage

This condition is governed by the following Equations (19-21).

$$T_{viecle} = \frac{L_{path}}{S_{viecle}} \quad (19)$$

$$L_{path} = 2\pi r \quad (20)$$

$$T_{fire} = \frac{r}{S_{fire}} \quad (21)$$

Where: $T_{vehicle}$: Time it takes by the firefighting vehicle so as to surrounds the fire. T_{fire}: Time it takes by the fire to reach the created path. L_{path}: The length of the created path. S_{viecle}: The firefighting vehicle average speed. S_{fire}: The fire average speed. r: The created path radius (the distance between fire and firefighting vehicle (path)).

Two extrapolation methods, polynomial and spline extrapolation, will be utilized to estimate the path shape at its position based on the available data points and corresponding equations (2 and 5), respectively. In terms of accuracy and error, the cubic spline extrapolation beats the polynomial extrapolation by 60%, as illustrated in Table 2.

Table 2: The comparison of path extrapolated distance and the estimation error by two extrapolation methods

Instant iteration (time unit)	The estimated iteration (time unit)	Path distance by the system (m)	Path distance at the estimated iteration using cubic spline extra. (m)	Error of estimated distance using cubic spline extra. (m)	Path distance at the estimated iteration using polynomial extra. (m)	Error of estimated distance using polynomial extra. (m)
100	186	230	211	19	208	22
200	324	523	497	26	482	31
300	488	821	788	33	764	48
400	596	1215	1178	35	1150	69

4. Results and Discussions

4.1. Simulating a real-fire spread mechanism based on the influencing factors

Figure (9), The two-dimensional dynamic response of the fire spread simulation is presented, which was influenced by four meteorological parameters, and data were collected at three in termittent time points during the fire spread period. These parameters are assumed to have the following values: humidity = 50 g / m3, temperature = 25 ° C, wind direction = 45 °, wind speed = 40 km/h.

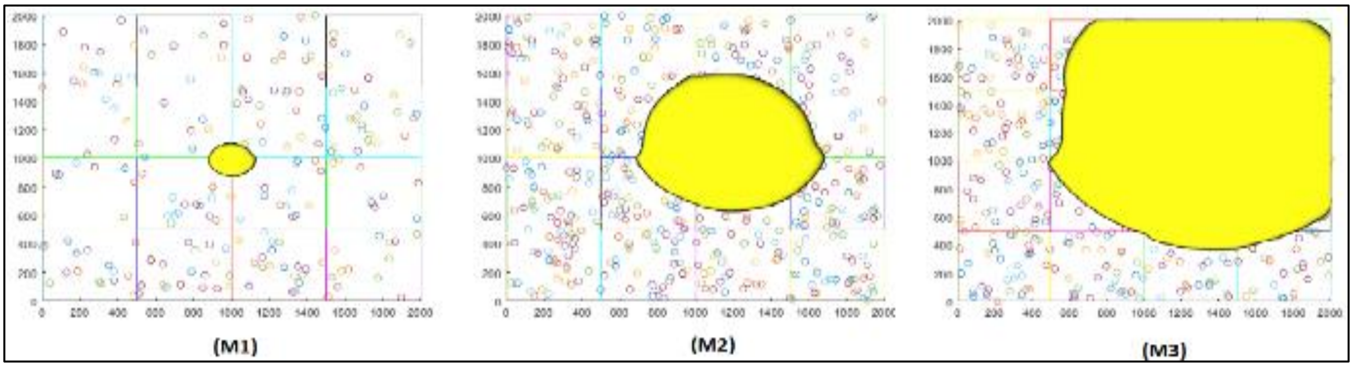

Fig 9: The two-dimensional dynamic response observed at three intermittent time points, denoted as M1, M2, and M3, of the fire spread process is analyzed with the assumed meteorological variable values

4.2. Detecting and forecasting fire propagation using Wireless Sensor Network algorithms

Figure (10) The four samples, M1, M2, M3, and M4, demon strate the fire's spatial and temporal propagation using Wireless Sensor Network technology. The analysis is based on the proce dures described earlier, which align with the fire's actual spread mechanism explained in the previous section. Figure (10) illustrates the 2-D dynamic response of fire spread in reality, as shown in yellow, and the 2-D detected and predicted fire area based on wireless sensor networks, shown in purple, at four in- termittent time samples M1, M2, M3, and M4.

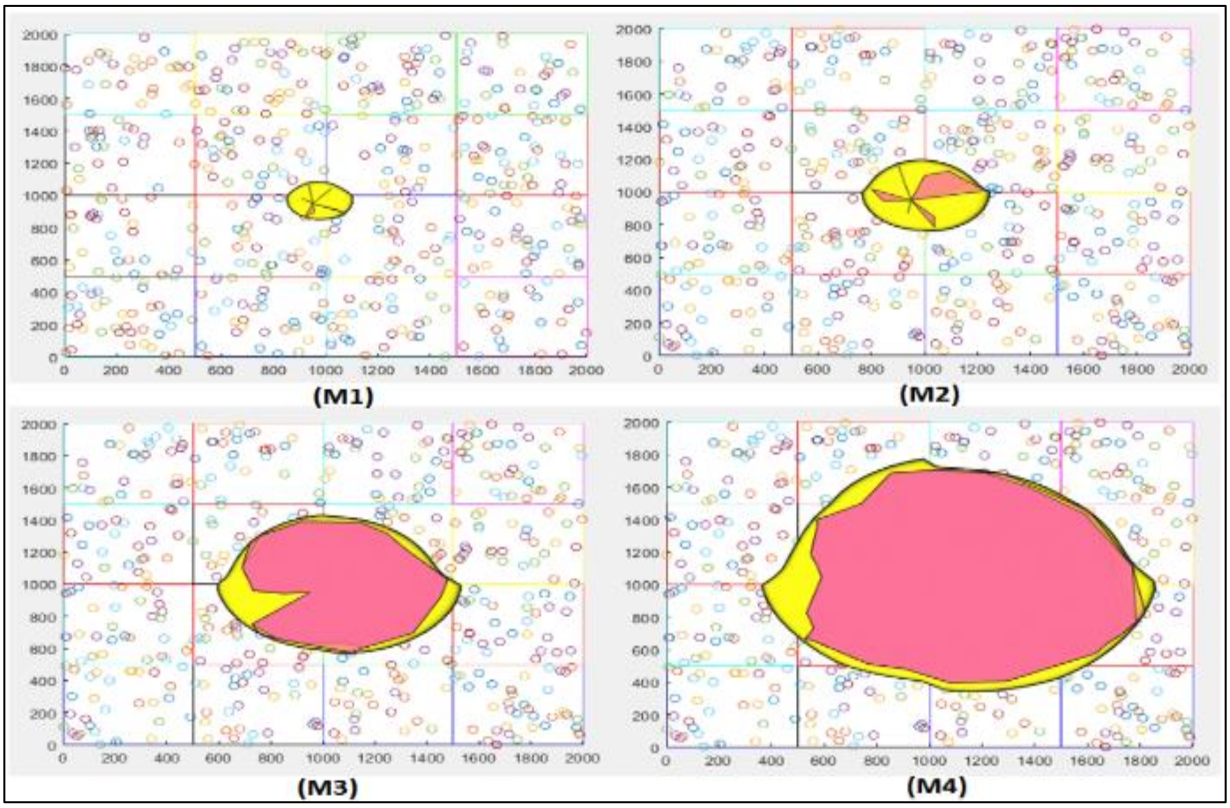

Fig 10: The fire area is presented at four intermittent time points M1, M2, M3, and M4. This is shown in two formats: the 2D dynamic representation of the actual fire spread in yellow, and the 2D detected and forecasted fire area based on Wireless Sensor Network monitoring in purple

Figure (11) shows the spatial extent of the fire increases over time in both the real-world simulation and the wireless sensor network detection scenarios. However, the sensor network-detected fire area is observed to be smaller than the actual fire extent for several reasons. In the real-world, the fire spread curve is smooth as it depends on various factors, while the sensor network detection results in a more uneven curve, with each peak indicating a new sensor notification of the fire's arrival.

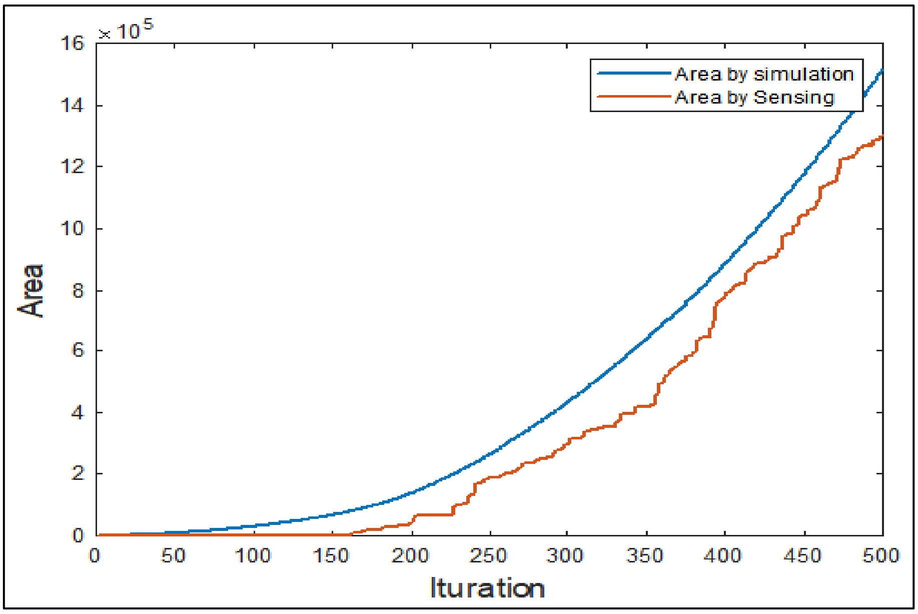

Fig 11: The area of fire spread by the sensing system and real fire

4.3- The improvement of the proposed WSN sensing system

Figure (12) illustrates the dynamics of fire propagation and expansion over time, as depicted by the enhanced WSN algorithm that relies on the sensing system, in contrast with an actual mechanisms of fire spread.

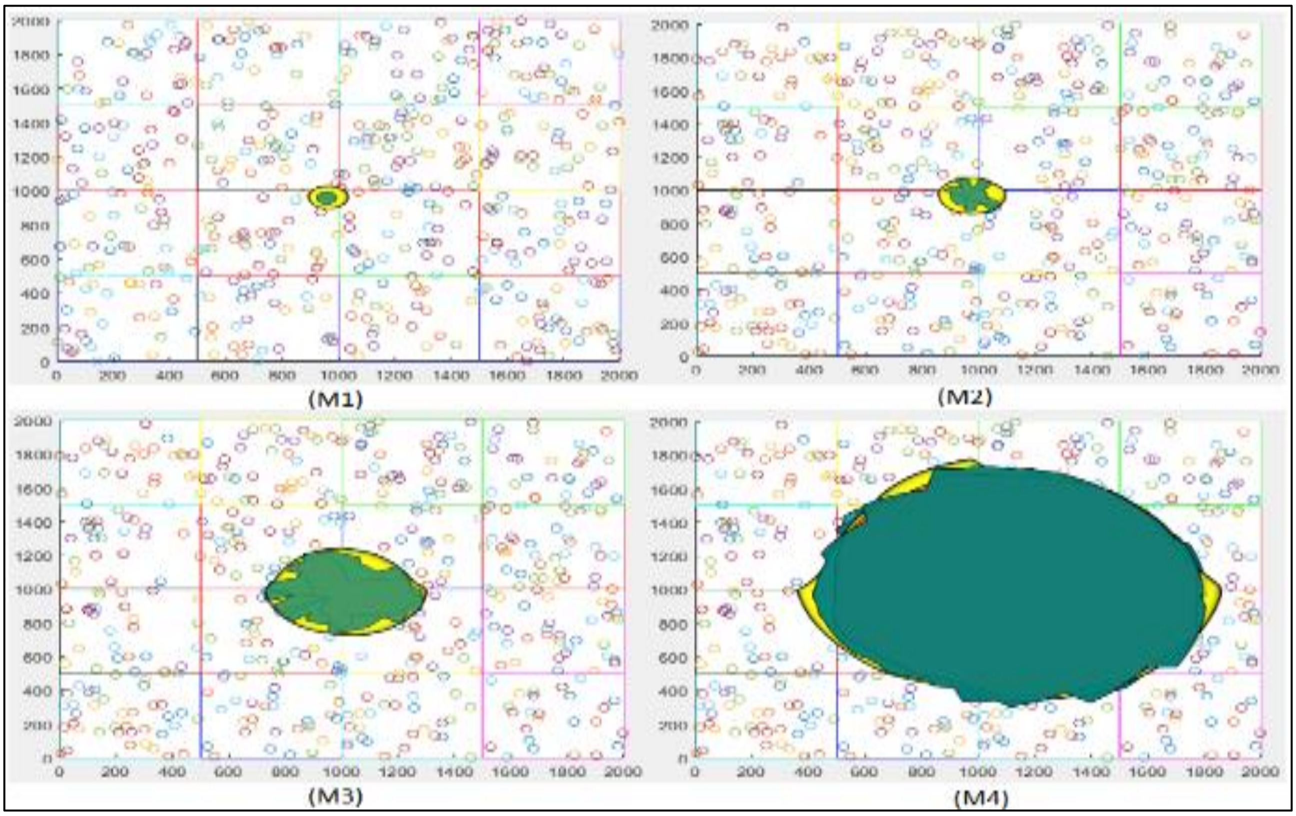

Fig 12: The fire area at four discrete time points M1, M2, M3, and M4 in two formats: the 2D dynamic fire propagation observed in reality depicted in yellow, and the 2D fire area detected and predicted using an enhanced wireless sensor network shown in green

By incorporating environmental factors that influence real-world fire propagation, which were simulated in an initial phase, through the calculations performed by the sensing algorithm, the accuracy of the wireless sensor network system is enhanced. Consequently, the improved system's prediction of the fire area closely aligns with the actual fire extent. Figure (13) compares the actual fire area with the predicted fire area using the sensing system and the fire area forecast by the enhanced wireless sensor network system.

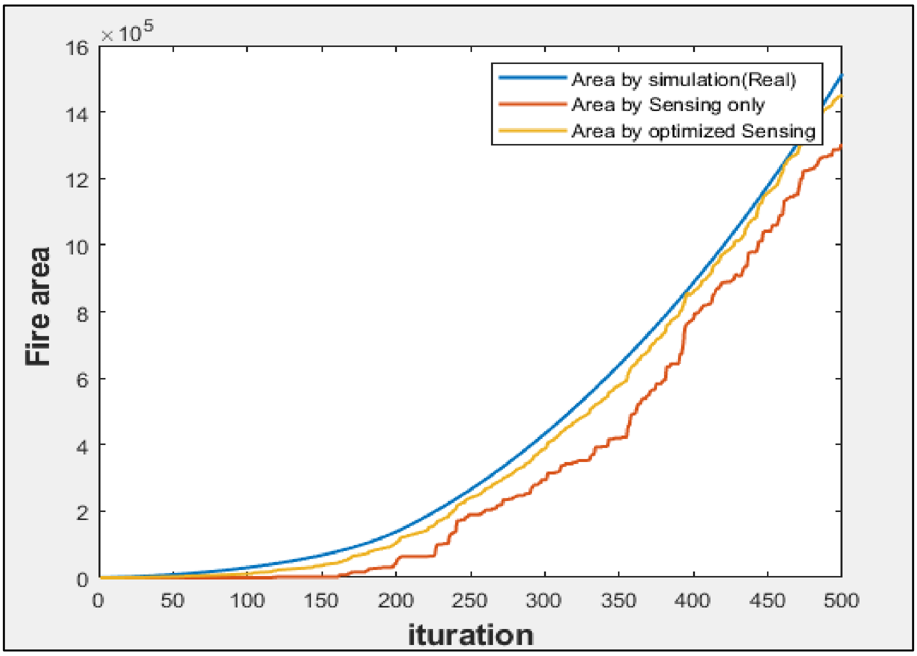

Fig 13: The predicted fire spread area by the two WSN systems compared with the real simulated fire spread area

The small margin of error and the close alignment between the predicted fire area from the enhanced WSN system and the actual fire area demonstrate the high level of accuracy attained by the improved system, with an improvement rate of approximately 6.6. Figure (14) examines the precision of the sensing system and the enhanced system, and analyzes how their performance is impacted by the increased distribution of nodes across the monitored area.

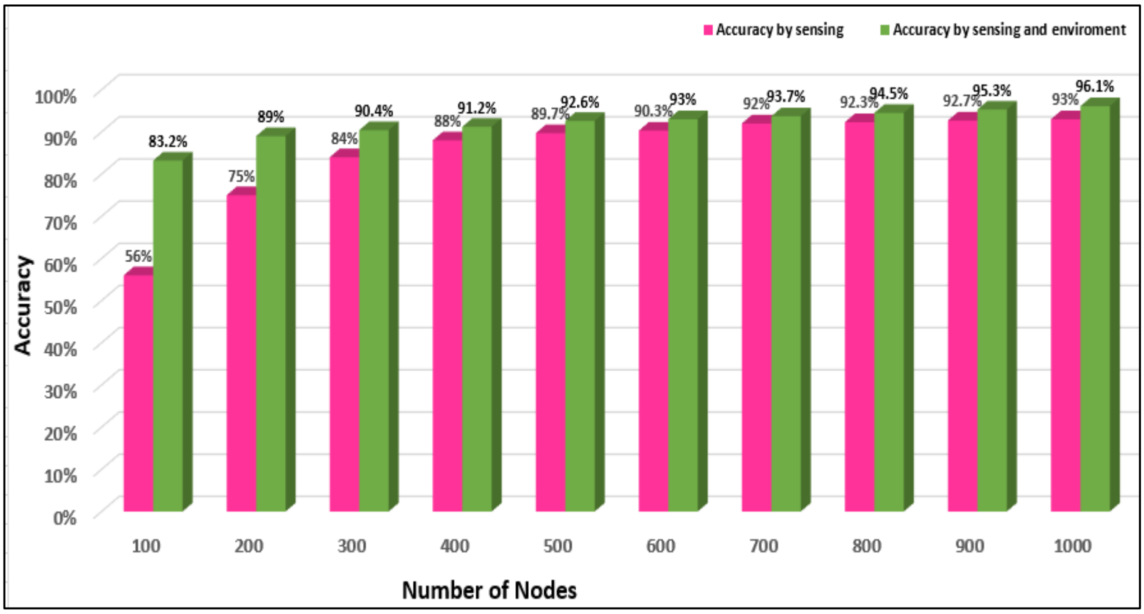

Fig 14: The correlation between the quantity of deployed sensor nodes and the precision of wireless sensor networks in two distinct systems

4.4. The created path for the firefighting truck to surround the fire

The path that has been created for the firefighting vehicle to surround the fire during a full cycle, this path is illustrated in Figure (15), where the figure shows four-time samples (iterations) of the fire spread (A, B, C, and D). The area of the expansion of the fire and the shape of the best path surrounding it. The mechanism by which this path is designed is explained in Section (3.4).

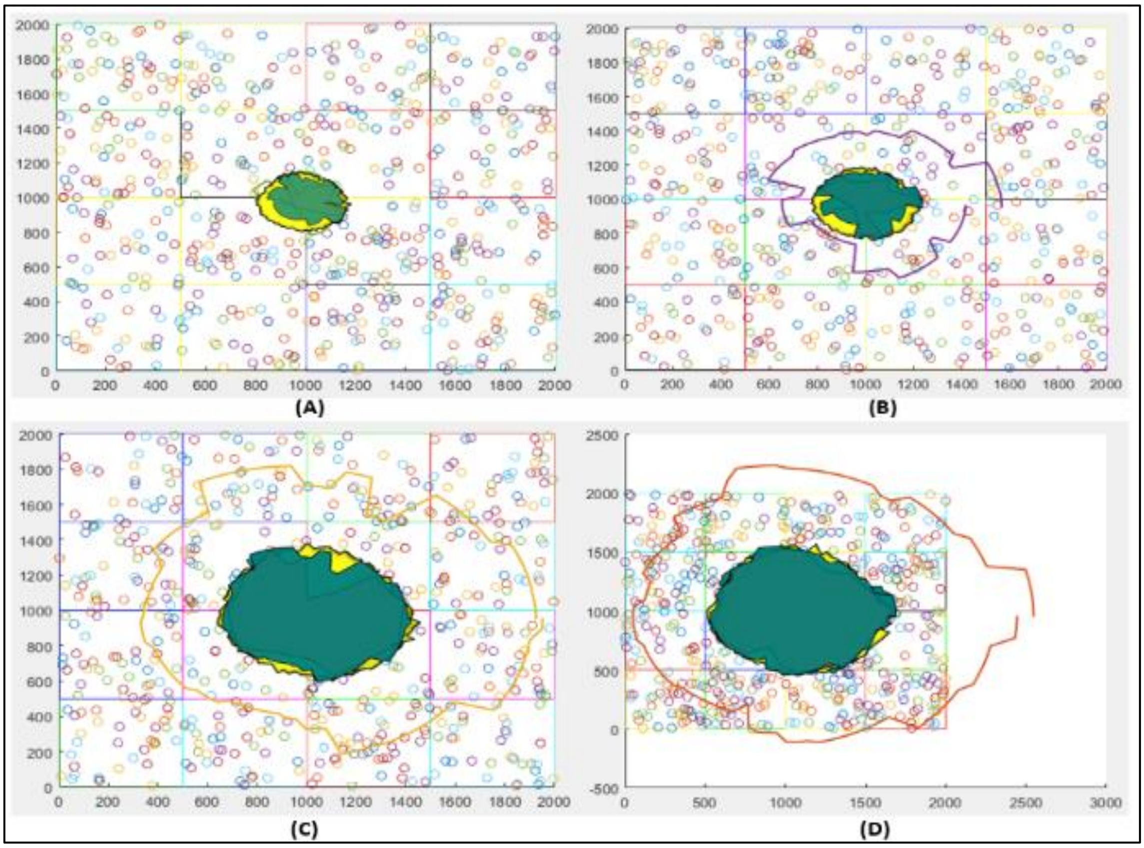

Fig 15: The created path for the firefighting vehicle

Figure (16) compares the accuracy of spline extrapolation and polynomial extrapolation techniques in predicting the shape of the extinguishing path. As explained by the figure, the error rate in polynomial extrapolation rises over time and with the addition of more sensor data, as the function becomes of higher degree. In contrast, spline extrapolation maintains a stable error rate because it employs a third-degree piecewise function.

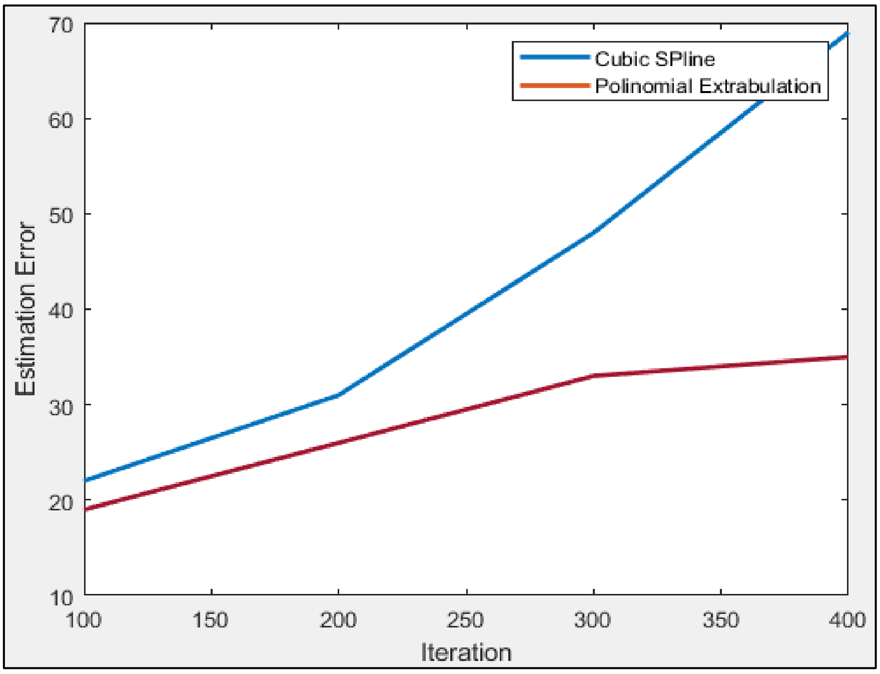

Fig 16: The error of estimated distance using spline and polynomial extrapolation

Conclusions and Future Work

This paper presents a framework for a wireless sensor net- work simulation that enables real-time detection and monitoring of forest fires using flame sensors. The framework is de- signed using the MATLAB programming environment. The study's findings and future research directions are summarized as follows: The proposed algorithm can enhance the performance of any existing or established wireless sensor system. The improved WSN system has demonstrated a notable enhancement in accuracy, achieving a 6.6% increase compared to the WSN sensing-only approach. The enhanced WSN sys- tem can attain satisfactory accuracy levels with a reduced sensor count, resulting in lower implementation costs. The proposed system can generate a secure route for firefighting vehicles, ensuring the complete containment and extinguish of the fire at a suitable pace without compromising a substantial land area. For future research, the system could be developed as a practical application. Additionally, the system is adaptable and can be adjusted or enhanced with simplicity. The system can also be adapted to accommodate new mathematical models for the spread of other physical processes, such as torrential rainfall or military troop movements.

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