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WILDFIRE DETECTION IN DRY FORESTS USING WSN-IOT SENSORS AND K-MEANS ALGORITHM

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ABSTRACT

Abstract- This paper presents the methodology employed for optimal deployment of Wireless Sensor Network (WSN) IoT nodes used for wildfire detection. The methodology focuses on utilizing the k-means clustering algorithm for determining the most efficient positions of WSN nodes. This chapter is organized into sections describing the problem statement, data collection, k-means clustering algorithm, performance evaluation, and the wildfire detection process. The primary objective of this study is to optimize the deployment of WSN IoT nodes in a specific geographic area to improve the accuracy and efficiency of wildfire detection. The problem involves determining the best positions for WSN nodes so that they can effectively monitor and report the occurrence of wildfires while minimizing energy consumption and communication latency.

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1. INTRODUCTION

Forests sometimes exist as unmanaged and neglected areas filled with many trees, seasoned timber, and fallen leaves. The combination of these components produces a fuel that generates an atmosphere favorable for the initial ignition spark of the fire. Several solutions exist to mitigate damage and losses, with the primary focus being on effective management and timely detection of forest fires. The user's text is "[12]". The user's text is "[12]". Hence, the primary focus of a forest fire detection system is the capacity to promptly detect fires, hence mitigating the severity of incidents. Therefore, it is imperative to carry out thorough monitoring of the area. Several methodologies have been proposed to monitor the occurrence of fires. Forest fires may be detected using many techniques, such as satellite monitoring. The Advanced High-Resolution Radiometer (AHRR) and the Medium Resolution Imaging Spectroradiometer (MODIS) are the primary satellites tasked with acquiring images. These satellites have the potential to capture images of specific areas of the Earth every two days. A longer duration has been allocated for extinguishing fires. Furthermore, fluctuations in the weather might significantly impact the quality of the satellite picture [13]. The wireless sensor network is an instance of an evolutionary technique that has experienced significant development over the years. Thanks to this incredible development, we may now utilize this technology for the early detection of forest fires. The wireless sensor network has several sensor nodes, each capable of detecting various phenomena such as temperature, humidity, and smoke, all of which are advantageous for fire detection systems. [14] However, these nodes must be deployed in an efficient and optimal manner in the area of interest in order to provide real-time fire detection with high accuracy. In this perspective, many works have been carried out on the problem of optimal deployment of sensor nodes [15]. This problem is to find the optimal location of sensor nodes under certain constraints such as: connectivity, coverage, cost of deployment, etc. However, most of these works do not take into consideration the representation of the area before the deployment phase. They accompany the deployment zone as a homogeneous, classic and uniform zone. However, it is important to define the potential positions of the sensor nodes and the target points to be covered in order to avoid solving the nodes in inaccessible positions such as the sea, the river, or areas without trees. Therefore, the phase of representing area of interest is essential for understanding the structure of the environment, defining the complexity of forest ecosystems over large areas and providing useful information such as the location of trees where fires can occur. occur. After the area representation phase, it is essential to choose the right deployment strategy in order to design a network of reliable and efficient sensors. The deployment strategy requires consideration of several criteria such as power consumption, area coverage, network lifetime, network connectivity, deployment cost, and node overlap. Often, these criteria are contradictory and operational compromises must be made during network design [16] This paper general aims to present the reader with an overview of the Internet of Things - IoT, which includes various aspects of Information and Communication Technologies (ICTs) and how AI can improve the performance of IOT in terms of transmission and quality of service. The specific aim of our work is to address the problem of data collection in IoT networks supporting heterogeneity, limited object resources and network scaling for optimal detection of physical phenomena in the region of interest such as wildfires. For this, we will present an algorithm for clustering and reorganizing the IOT sensors for better routing. Next, the following clustering algorithm (K-means) will be discussed. The discussion will address not only the advantages of using such algorithms, but also the shortcomings of it and how to overcome these shortcomings. After that, we will discuss the concept of fuzzy logic and the role it plays in the proposed routing system. Finally, we will present an approach that has two phases: a phase of representing the area of interest and a phase of optimal deployment of sensor nodes. The first phase is based on K-means clustering. Its objective is to determine the points of interest to be covered by the sensor nodes. Regarding the deployment phase, it is based on fuzzy logic. Its main objective is to optimize the location of sensor nodes by maximizing coverage and minimizing the number of nodes deployed while ensuring full network connectivity and minimal overlap.

2. RELATED WORKS

In recent years, there have been very few attempts made to manage forests through the usage of wireless sensor networks and smart sensors that are based on the internet of things. These initiatives have been exceedingly restricted. A system that utilizes machine learning, cloud storage, and Internet of Things sensor setup was proposed by Zope et al. [15] to evaluate historical data on forest fires and make predictions regarding the likelihood of forest fires occurring in the future. This system makes use of real-time data that is input into the system through the use of Internet of Things devices and sensors. When real-time data is collected, the method that is described in [15] also identifies a trend based on helpful and distinctive features such as location, altitude, and temperature to anticipate the risk of forest fires. This detection is done to prevent forest fires from occurring. These measures are taken to forestall the occurrence of fires in the forest. Mushnaq et al. [16] suggested a unique approach for the detection of wildfires that takes use of unmanned aerial vehicles (UAVs) and networks that are connected to the Internet of Things (IoT). This method was developed by the authors of the study. The first objective is to investigate the performance and dependability of UAV-IoT networks for wildfire detection. The second objective is to provide guidelines for optimizing the UAV-IoT network in order to increase the possibility of fire detection while preserving tight system cost limitations. In essence, these are the primary objectives. The primary objective of the authors is to maximize the density of Internet of Things devices and the number of unmanned aerial vehicles (UAVs) covering the forest area in such a way that a limited limitation on the likelihood of wildfire detection is maximized within a specific amount of time and system cost. This is the primary focus of the authors. After the fire has started to spread, Internet of Things sensors that are situated within a certain radius of the blaze are able to detect it at any time, according to the authors of the article [16]. Kaur et al. [17] suggested a system for detecting and forecasting wildfires that is both energy-efficient and combines technologies like the Internet of Things (IoT), fog, and cloud computing. This approach was developed to improve disaster management. With the variance analysis and Tukey's post-hoc test-based energy conservation mechanism, resource-constrained sensors are guaranteed to have a longer lifespan at the beginning of the process. Adjusting the sample rate of wildfire influent parameters (WIPs) at the fog layer is the methodology that is utilized to achieve this goal. Using principal component analysis (PCA), it is feasible to reduce the quantity of work that is currently being done (also known as "work in progress"). At the cloud layer, the Naïve Bayes (NB) classifier and the seasonal auto-regressive integrated moving average model are applied for the aim of predicting and forecasting wildfire susceptibility levels in forest terrain. This is done to ensure accurate predictions and forecasts. Additionally, it is feasible to make a prediction regarding the size of the forest that has been burnt by using support vector regression.

3. MATERIALS AND METHODS

We go into some of the materials (section 4) and the history, architecture, and layout of the suggested system in this part:

3.1. internet of things

Originating in earlier technologies, namely mobile ad hoc networks (MANET) and wireless sensor networks (WSN), the Internet of Things represents a technological revolution [1]. The sensor is the primary element of these networks. A sensor is a little device that can watch and respond to events that is included in a personal area network (PAN) and has components of detection, measurement, computation, and communication.

3.2. IoT Architecture

It is crucial to establish a shared model of the architecture of the Internet of Things because it contributes to the creation of interoperable Internet of Things systems by providing standards, implementations, and viewpoints. When it comes to the Internet of Things, there is not yet standardized architecture in place. Despite this, a number of research groups and academic institutions have developed architectural principles for the Internet of Things. The following are some examples of examples of common designs that are now accessible for the Internet of Things. In the initial design, which was described in full in [10], the authors offered a hierarchical structural model that consisted of three layers. The perception, network, and application layers were the names given to these layer categories. In the Internet of Things, the perception layer, which is located at the bottom, is the sensory organ that is responsible for processing information. Identifying artifacts is another objective, in addition to the collection of information. Components that make up this layer include radio frequency identification (RFID) tags, two-dimensional barcode scanners, terminals, global positioning system (GPS) units, cameras, sensors, and sensor networks. In the hierarchy, the network layer is the second layer that is present. It is the "core" of the Internet of Things that this layer is located at. After the information has been received from the perception layer, it is subjected to an analysis, and then it is sent on to the application layer through the transmission process. The information center, the intelligent processing center, the internet network systems, and the network management center are only few of the components that come together to form the network layer. The third layer is known as the application layer, and its primary purpose is to fulfill the socio-business objectives of the Internet of Things (IoT). Additionally, it provides an explanation of the specific job that is linked with each node individually. The Internet of Things (IoT) and industrial technology are both represented by this layer, which also includes a combination of industrial needs and system management. This layer is a depiction of the interaction between the two industries. A visual representation of the architecture that is being presented may be found in Figure 1.

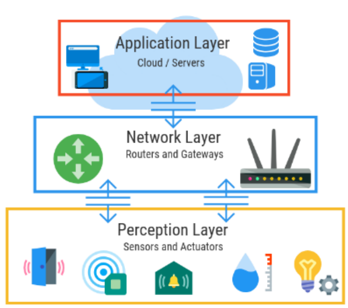

Figure 1: Three-layer architecture model [10].

Dijlah Journal of Sciences and Technology (DJST)
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3.3 IOT AND NATURAL DISASTER PREDICTION

Damage caused by natural disasters such as landslides, floods, fires, and volcanic eruptions, as well as the devastation that these catastrophes generate, are worldwide concerns that result in monetary and human losses. They also generate destruction. The climatic conditions of the world are changing, which is making this problem even more severe, and it is especially prevalent in residential areas in metropolitan areas. Certain places are facing more severe ecosystem degradation as a consequence of pollution and a lack of planning, which is producing negative impacts on the ecology and causing changes to the temperature of the area. All of these factors are contributing to the degradation of the ecosystem. For example, one could argue that even very little shifts in climate have a major influence on the frequency and severity of incidents of flooding. This is because climate is a very complex system. These changes include, for instance, the creation of heat islands, which ultimately results in a shift in the pattern of rainfall that occurs in the region. hold the conviction that the phenomena known as global warming is the primary cause of the rise in the frequency of natural catastrophes, and that the monitoring of climate through the utilization of sensors is a technology that is not only feasible but also essential for the purpose of producing timely predictions and alarms. for the purpose of rendering decisions about a wide range of natural calamities, such as earthquakes, landslides, and floods. As an illustration, floods influence more than 102 million people all over the world each year, and it is anticipated that this figure will continue to increase in the years to come. This is because nations that are still in the process of development and metropolitan regions are the ones that are most vulnerable to flooding. In recent years, Turkey has experienced a shift in climate, which has led to the environment being more vulnerable to natural catastrophes. This has resulted in the ecosystem becoming more endangered. Specifically, these are the features that Turkey possesses. In addition to restating what was mentioned previously, they note that the cures that are currently accessible do not greatly lessen the amount of damage that is caused by floods. Although it is not feasible to halt many natural disasters, such as floods, it is possible to minimize and control the consequences of these catastrophes if they are anticipated in advance. Floods are one example of a natural disaster that cannot be stopped immediately.

4. PROPOSED METHOD

a. Data Collection

To simulate the environment for the deployment of WSN IoT nodes, a dataset consisting of geographical and environmental features of the study area is required. This dataset may include information on vegetation, topography, and meteorological conditions, which can influence the likelihood and spread of wildfires. The data can be obtained from satellite imagery, geographical information systems (GIS), and local weather stations.

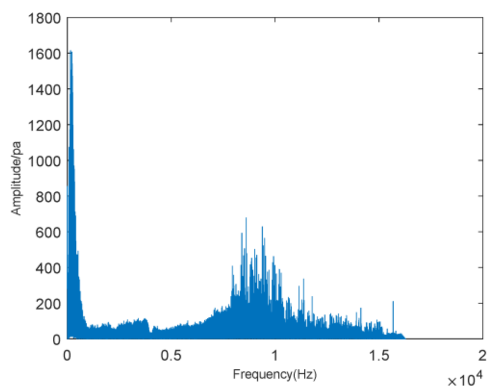

Figure 2 Widlfire data simulated in MATLAB.

The output figure above shows a table with three columns: "Unburned", "Burning", and "Burned". Each row represents an iteration of the simulation, displaying the number of cells in each state at that point in time. Unburned: Cells in this state represent areas of the forest that have not been affected by wildfire. Burning: Cells in this state represent areas of the forest that are currently on fire Burn.

Dijlah Journal of Sciences and Technology (DJST)
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4.2 K-Means Clustering Algorithm for Optimal Deployment

The k-means clustering algorithm is used in this study for optimal deployment of WSN IoT nodes. The algorithm aims to partition the study area into k clusters based on the similarity of data points (node positions) within each cluster.

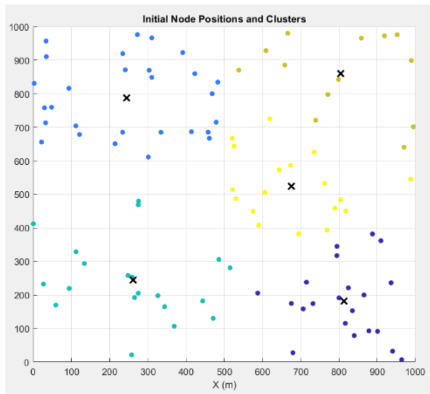

Figure 3 Node clustering using K-means algorithm.

The algorithm follows these steps: Initialize k cluster centroids randomly within the study area. Assign each data point (node position) to the nearest centroid. Update the centroids by calculating the mean position of all data points assigned to each centroid. Repeat steps 2 and 3 until convergence is achieved, i.e., the centroids no longer change significantly. After obtaining the k clusters, the centroid of each cluster represents the optimal position for the corresponding WSN IoT node. By deploying nodes at these centroids, the network can achieve improved coverage and efficiency in wildfire detection.

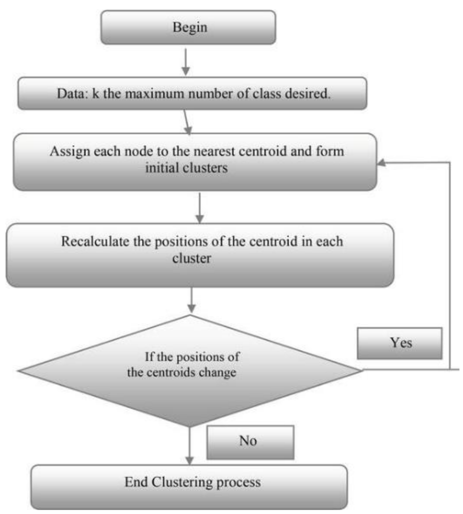

Figure 4 K-means clustering and routing process.

4.3 Performance Evaluation

To evaluate the performance of the proposed method, the following metrics are considered: Accuracy: The ability of the deployed WSN IoT nodes to correctly detect and report wildfires. Energy Consumption: The total energy consumed by the WSN IoT nodes for data transmission and reception. Communication Latency: The time taken for information to travel between WSN IoT nodes and the central monitoring station. These performance metrics are assessed through simulations, comparing the results of the k-means algorithm with other deployment strategies or random deployments.

In the context of Wireless Sensor Networks (WSN) used for wildfire detection, the following metrics are commonly used to evaluate the performance: accuracy, error rate, and energy consumption. Here's an explanation of how to calculate each of these metrics using equations:

Accuracy:

Dijlah Journal of Sciences and Technology (DJST)
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Accuracy is the measure of how well the WSN can correctly detect and report wildfires. It is calculated as the ratio of the number of correctly detected events (true positives) to the total number of events, which includes both correctly detected events (true positives) and missed events (false negatives).

$$Accuracy = (True\ Positives) / (True\ Positives + False\ Negatives)$$

Error Rate:

Error rate is the measure of the mistakes made by the WSN in detecting wildfires. It can be calculated as the sum of false positives (when the WSN reports a wildfire, but there isn't one) and false negatives (when the WSN fails to report a wildfire that is present) divided by the total number of events, which includes true positives, true negatives, false positives, and false negatives.

$$Error\ Rate = (False\ Positives + False\ Negatives) / (True\ Positives + True\ Negatives + False\ Positives + False\ Negatives)$$

Energy Consumption:

Energy consumption is the total energy used by the WSN for various tasks, including sensing, data processing, and communication. Energy consumption can be calculated by summing the energy consumed by each sensor node in the network. The energy consumption for a single sensor node can be calculated as:

$$E\_node = E\_sensing + E\_processing + E\_communication$$

Here, E_sensing is the energy consumed by the sensor for sensing the environment, E_processing is the energy consumed for data processing and decision-making, and E_communication is the energy consumed for transmitting and receiving data between nodes and the base station. To calculate the total energy consumption for the entire WSN, you would sum the energy consumed by each node:

$$E\_total = \Sigma\ E\_node\ (for\ all\ nodes\ in\ the\ network)$$

Keep in mind that these equations are general, and specific implementations of WSNs might have different factors affecting accuracy, error rate, and energy consumption. It is essential to consider the characteristics of the particular WSN under study when evaluating these metrics.

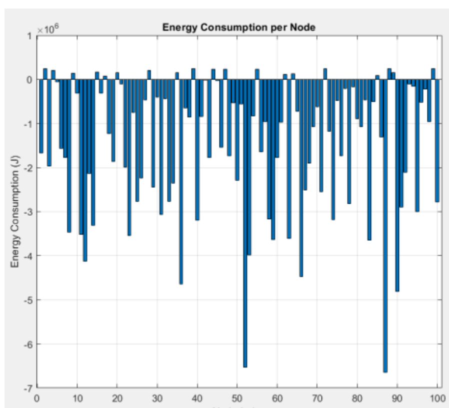

Figure 5 Energy consumption by each node of the WSN-IOT

4.4 Wildfire Detection Process

The deployed WSN IoT nodes are equipped with sensors to detect signs of wildfires, such as temperature, humidity, smoke, and infrared radiation. When a node detects a potential wildfire based on predefined thresholds, it sends an alert to the central monitoring station. The monitoring station collects data from multiple nodes to determine the location, size, and intensity of the wildfire. It also initiates appropriate actions, such as activating firefighting resources and issuing evacuation orders.

Dijlah Journal of Sciences and Technology (DJST)
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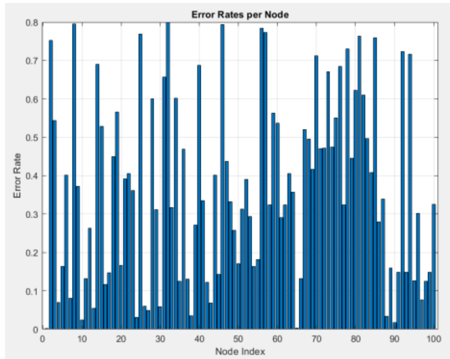

Figure 6 Error rate of detecting wildfires.

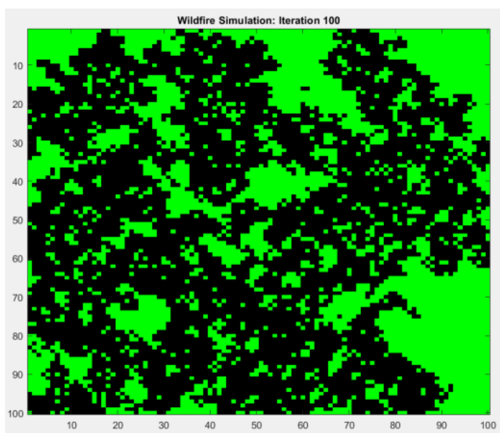

Figure 7 Wildfire simulation in MAtlab

The figure shown in the previous code displays the progress of a simulated wildfire spreading through a forest. The forest is represented as a grid, where each cell can be in one of three states: Unburned (0): Cells in this state represent areas of the forest that have not been affected by wildfire. In the figure, unburned cells are displayed in green. Burning (1): Cells in this state represent areas of the forest that are currently on fire. In the figure, burning cells are displayed in red. Burned (2): Cells in this state represent areas of the forest that have been burned by the wildfire. In the figure, burned cells are displayed in black. The simulation uses a Cellular Automaton (CA) model to simulate the spread of wildfire. At each iteration, the update Forest function updates the grid based on a set of rules that govern the fire's spread. The figure is updated at each iteration, showing the current state of the forest grid. The title of the figure indicates the current iteration of the simulation. As the simulation progresses, you will observe the wildfire spreading through the forest, with burning cells (red) turning into burned cells (black), and unburned cells (green) igniting based on the fire spread probability defined in the code. The figure provides a visual representation of the wildfire's impact on the forest over time**.**

5. Conclusions

This paper presented a comprehensive study on the design, development, and implementation of an integrated wildfire detection system using Wireless Sensor Networks (WSNs) and the Internet of Things (IoT). The primary goal was to create an efficient, real-time, and reliable system for early detection and monitoring of wildfires to minimize the associated risks and damages. The main findings and contributions of this work can be summarized as follows: A comprehensive review of the current state-of-the-art in wildfire detection technologies was conducted. This review highlighted the limitations and gaps in existing solutions and provided a solid foundation for the proposed integrated approach. A novel architecture for a WSN-based wildfire detection system was designed, incorporating specialized sensor nodes, data fusion techniques, and efficient communication protocols. This design facilitated timely detection of wildfires and reduced false alarms. An IoT-based framework was proposed to connect the WSN with remote monitoring and control centers, ensuring seamless data transmission, visualization, and analysis. This framework allowed for enhanced decision-making capabilities and improved emergency response times. A thorough evaluation of the proposed system was conducted through simulations and real-world deployments, demonstrating its effectiveness in early wildfire detection, reducing response times, and providing accurate information to emergency responders.

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