

Energy-efficient wireless sensor networks for disaster management using hybrid technique

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Abstract

The paradigm of WSNs acted as a powerful source of data in real time for disaster management to make better and punctual decisions. In the proposed paper, an effort has been carried out to present a hybrid approach combining Genetic Algorithm, Artificial Neural Networks, and Particle Swarm Optimization: Investigating the Performance of WSNs and the Energy Efficiency in the Time of Tragedy. The design here will focus on optimal routing paths that will be energy-aware, with respects to robust network performance metrics such as latency, delivery ratio, drop rates, throughput, energy usage, node lifetime, overhead, and overall system efficiency. The proposed framework is evaluated by simulations in the NS2 simulator, comparing its performance against traditional PSO and GA models. Thus, the results indicate the hybrid approach greatly improves network efficiency as well as reliability. It thus proves to be an efficient approach for energy-efficient deployments of WSN in applications related to disaster management.

Subject Classification: 94C12, 68M10, 68T07.

Keywords: *Energy efficient, Wireless sensor network, Particle swarm optimization algorithm, Neural network.*

1. Introduction

Sensor nodes are essentially self-sufficient, low-powered devices with limited computing capacity for data gathering and transmission through radio signals in WSNs [1]. WSNs are ubiquitous and have very widespread applications ranging from climate forecasting and temperature to home automation [2]. WSNs possess no fixed form and therefore have an inherent need for tools such as self-blue printing and adjustment for possible anomalies [3]. Research is focused on optimizing sensor capacity with respect to restraining transparency, information drift, energy dissipation, and structural destruction [4]. An array of techniques has been proposed aimed at energy-usage-based disaster control in WSN. Most researchers have employed machine learning approaches such classifiers are, for example, Support Vector Machines (SVM), Bayesian Networks, Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) [5]. In addition to this, the AI is combined with optimization models, like the Firefly Algorithm (FA), PSO, and Whale Optimization Algorithm (WOA), in order to enhance the management process [6].

2. Related work

WSN has been taking much attention in developing energy-efficient methodologies. Methods include the automation model, dynamic

detection, and the hybrid clustering and routing (HCR) conference [7]. The ARNN model is effective in reducing transmission among power and precision. However, the current algorithm may consume vital energy due to lost objective events [8]. Singh et al. [11] have derived a dynamic discovery system GA, an integration of reach and action towards modified energy efficiency [9]. This system fulfills several requirements such as increasing intra-cluster distance, using centre energy, reducing hop count, and choosing active centres for CHs [10]. Kumar et al. have introduced compound compilation and operation computation regarding hub development and communication. The hybrid clustering and routing (HCR) conference proved that the geographical system provided by HCR is reachable and efficient [11]. Satyapriya et al. designed a head-to-head computation for energy efficiency; the designed head-to-head computation takes into account several factors including bunching coefficient ranges, distance centre, correspondence distance, and residual power of sensor centres [12]. Ajmiet al. provided a hybrid MAC protocol. with an energy-efficient hybrid MAC based on contention that proved better than later MAC traditions [13]. The study, though found impedance issues brought about by the mix of half-race MAC, Zigbee and WSN [14]. If indeed shortcut development strategies in WSM focus on shortcut development, then it may shorten an organization's lifespan during source to target correspondence and maximize energy use [15].

3. Proposed System

A WSN is an infrastructure that is self-configuring, analyzing exterior and conservation status, such as moisture, temperature, pollutants, and

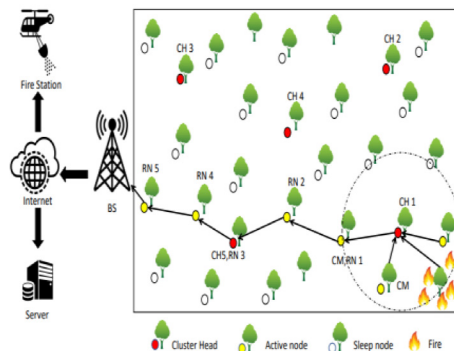


Figure 1
WSN Structure

movement, and data diffusion. In this paper, an analysis of disaster management was done using WSN architecture, by utilizing an ANN with Artificial Object Orientation (AOA) in order to optimize energy efficiency. The WSN infrastructure is illustrated in Figure 1.

The approach calculates procedure efficiency by keeping the position of the sink node in mind. Energy drainage can be measured using the distance function from the CH. ANN refers to a technique applied for modeling utility with multiple inputs and outputs. Layers of inputs, hidden, and outputs characterize them, and feedforward neural networks (FNN) is a common structure amongst them. This evaluation of performance happens through noisy input - output vectors that decrease errors in classification

It is a centralized approach in which the routing as well as clustering is done by the sink. For optimal scheduling and saving energy, TMAC procedure is used in this approach. The overall count of CHs in the network is calculated by multiplying the latter by 5%. During the transmission and reception procedures, the minimum RSSI is set to 97db. In this approach, the network is homogenous with absolute nodes whose power commences with the same value. The sink node only knows the position, whereas nodes do not know their location. The hidden layer weights are created by multiplying the input layer weights with the network's inputs, the threshold parameter being denoted by Figure 2.

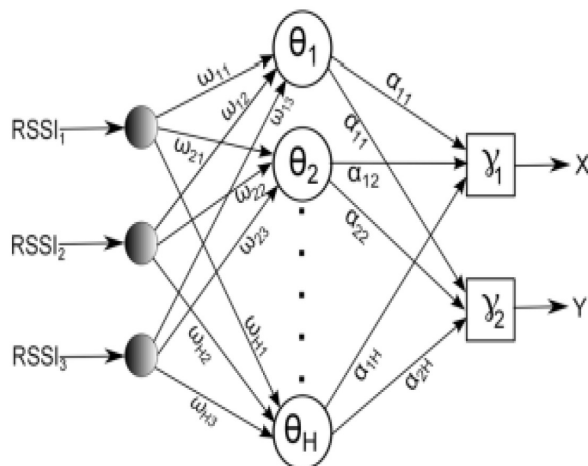


Figure 2
ANN Structure

$$n_i = \sum_{j=1}^3 w_{ij} \text{RSSI}_j + \theta_i \quad (1)$$

The output from the net is converted through the non-linear activation function to provide the output for the hidden node. The output of the hidden node needs to be monotonically increasing, bounded, continuous, and differentiable. Log sigmoid and hyperbolic-tan sigmoid are most commonly used functions. Hyperbolic-tan has been chosen because of the distinctive function having symmetry. The parameters associated with power are multiplied by the output of the hidden node and summed together to create the output of the network.

$$x_i = \sum_{j=1}^h \alpha_{ij} \sigma(n_i) + \gamma_i \quad (2)$$

The weights of the network are set to very small unsystematic standards. Inputs are sent as RSSI values for the forecast of the transmitters integration in Motes.

PSO is employed in optimizing the energy consumption of WSNs. Programming power at each sensor node as well as its data routing path is tuned using PSO so that there will be a reduction in terms of energy usage without compromising network connectivity and information integrity. The fitness function of the PSO calculates just how much energy the network consumes overall, expressed as:

$$E_{total} = \sum_{i=1}^n E_i \quad (3)$$

Where E_i is the energy used by the i -th node and N is the overall count of nodes. The position and speed of each element in the PSO algorithm are modernized in line with the following equations:

$$v_i(t+1) = wv_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t)) \quad (4)$$

Where v_i refers to the velocity of particle i , x_i is the site of element i , p_i is the personal finest place of Element i , g represents the optimal global position, w denotes the inertia factor, c_1 and c_2 are the personal and group influence factors, and r_1 and r_2 are stochastic values ranging from 0 to 1.

This enhances network configuration by choosing some optimal sensor nodes and operational parameters through mutation operations, selection, and crossover. The fitness function evaluates network performance in terms of coverage, connectivity, and energy efficiency. The selection method uses the roulette wheel and maintains genetic diversity using the mutation.

$$F = w_1 \times \text{Coverage} + w_2 \times \text{Connectivity} - w_3 \times \text{Energy Consumption} \quad (5)$$

PSO, ANN, and GA are combined in a mixture method for an energy-efficient WSN for disaster management. The ANN processes disaster events, PSO optimizes energy consumption, and GA refines network configuration. This approach ensures accurate disaster prediction, minimal energy consumption, and optimal network performance, providing a comprehensive solution for disaster management using advanced computational techniques and WSN technology.

4. Experimental Result

Table 1 shows the result, then continue the results of the proposed methodology were evaluated using the NS2 simulator and conventional

Table 1
Performance metrics used to evaluate

Metrics	Model	Minimum Drop Rate (packets)	Maximum Drop Rate (packets)
Energy consumption	Proposed Model	2000	2500
	PSO Model	2000	8000
	GA Model	4000	8000
Lifetime comparison	Proposed Model	4500	20000
	PSO Model	2000	5000
	GA Model	2000	4000
Overhead	Proposed Model	6000	8000
	PSO Model	10000	12000
	GA Model	13000	10000
Throughput	Proposed Model	20000	32000
	PSO Model	6000	11000
	GA Model	4000	8000
Latency	Proposed Model	5	20
	PSO Model	10	26
	GA Model	10	35
Drop rate	Proposed Model	4	5
	PSO Model	10	12
	GA Model	12	16
Delivery Ratio	Proposed Model	0.6	0.9
	PSO Model	0.7	0.5
	GA Model	0.1	0.8

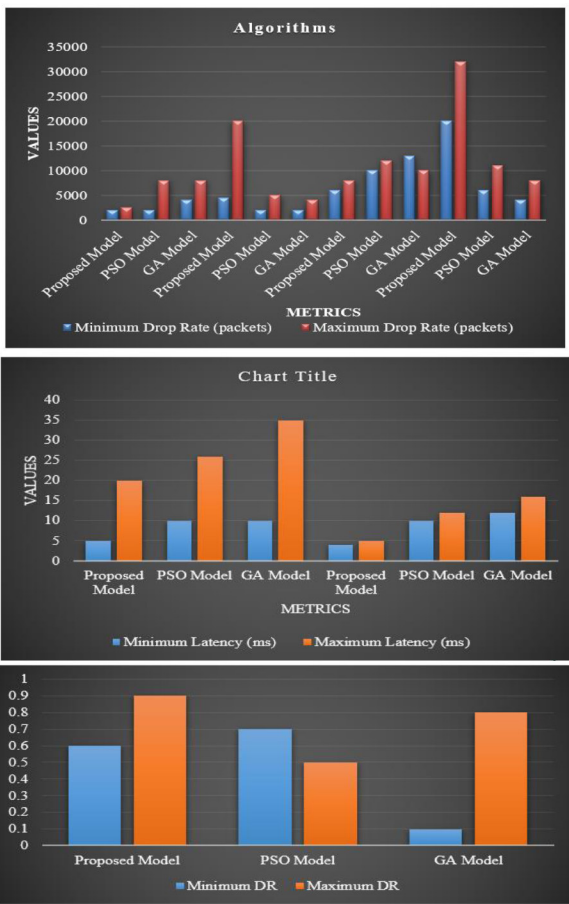


Figure 3
Comparison of Various Metrics

methods like GA and PSO algorithms. The methodology aimed to quantify optimal routing paths in WSN infrastructure, focusing on latency, delivery ratio, drop, throughput, energy usage, lifetime, and overhead.

Figure 3, proposed methodology focuses on energy usage minimization and load balancing, with the AOA fitness tracking the optimal path to achieve these objectives. The developed approach has been found to have low latency due to its optimal organization. The node density (DR) of the designed model is at least 0.6, while the PSO and GA models have a base DR of 0.7 and a large DR of 0.5 respectively. The presented model with a high DR is selected as the best arrangement, providing better outcomes compared to other existing techniques.

The nodal drop incurred by different methods is also evaluated, with the presented framework achieving a low drop degree of 2000 and an extreme drop rate of 2500. The energy usage of the presented approach is 4, and 5, respectively, at its low and large cases, indicating that the developed model provides less energy consumption compared to other approaches. The design with the largest lifespan of the nodes in the network is chosen as the best, with the developed methodology achieving a lifespan of 4500 and 20000, respectively. The control overhead associated with the node in the network is chosen as the best model, with the semi-racial calculation minimizing its overhead. The performance of the structure should be kept undeniable is selected as the optimal model, with the proposed calculation reducing the efficiency of the structure. The PSO calculation has a base performance of 11000, while the GA calculation has a base performance of 4000 and a very intense performance of 8000.

5. Conclusion

WSN contains a sensor node network, which traces and examines the state of the substantial background and stores the information in an essential locality. In smart cities, one of the crucial applications is the disaster management. As a result, prolonged WSN lifetime is critical to ensuring system availability. The clustering is often considered one of the effective routing mechanisms as it increases the WSN's energy efficiency. As a result, ANN-AOA is created in this paper to monitor environmental conditions in the agricultural field. The model was developed to enhance the performance in terms of energy efficiency of WSN. AOA and ANN are hybridized into the proposed technique. In the proposed method, an optimal routing architecture is utilized for improving energy efficiency. Using ANN, it enables the operation to be even more energy efficient. It applies AOA in the ANN to determine the best path to take. The designed algorithm will be tested using the NS2 simulator. It will also compare different kinds of strategies with other proposals, like PSO and GA. Presentation metrics for this target include energy consumption, DR, latency, lifetime of a network, overhead drop and throughput.

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