Energy Efficient Underground Wireless Sensor Networks for Disaster Analysis in Hill Stations

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The emerging growth of wireless sensor networks (WSN) systems provides various benefits over the data transmission at different environments. Remote monitoring systems are important to make continuous evaluation of environments, healthcare, safety, emergency response and smart analysis. Underground wireless sensor networks (UGWSN) are increasing in recent innovations for detection of various emergency condition and to provide early alert to the peoples. Even though UGWSN models face various challenges in terms of installations and maintenance, dynamically changing environment, sensor life span affected by environment, noise etc, power constraints act as important problem in having sustainability. The proposed approach considers an energy efficient underground wireless sensor network (UGWSN) using AI-optimized predictive neural computing (AI-OPNC) models early detection and analysis of disasters leads in hill regions. The primary goal enforced on detection of disaster triggers such as earth quakes, land slide dynamics and to analyse the occurrence stamps using AI-OPNC model, on the other hand the network health is monitored through network health keeper. The proposed system performance is measure in two phases such as network performance in terms of energy efficiency, data loss etc and the performance of AI-OPNC in terms of predictive analysis through accuracy. The proposed system achieved 95% accuracy; energy efficiency increases 10% with respect to data loss suppressed 8% using UGWSN nodes.

Keywords: Artificial intelligence, Wireless communication, Underground sensor network, Disaster management, Internet of things.

in: *Advancements in Communication and Systems*. Ed. by Ashish Kumar Tripathi and Vivek Shrivastava. Computing and Intelligent Systems, SCRS, India., 2023, pp. 55–63. DOI: https://doi.org/10.56155/978-81-955020-7-3-5

1 Introduction

The Internet represents a dynamic evolution in communication technology, serving as a versatile platform for diverse communication models aimed at achieving the swiftest data transfer possible. When combined with sensor-based communication networks, it facilitates highly efficient communication within the Internet of Things (IoT) framework[1]. The architecture of IoT systems excels at establishing connections with a multitude of field nodes, enabling rapid and effective data transmission in remarkably brief timeframes. The implementation of diverse internet-connected systems involves a combination of sensors employed for gathering environmental data, adaptable cloud-based solution frameworks tailored to the specific application, and the integration of various high-performance computing devices within the cloud infrastructure[2]. The system architecture is structured around a network of seamlessly interconnected sensors, maintaining a continuous flow of environmental information, which is transmitted across the communication network without interruption. UGWSN are implemented in precision agriculture to monitor the soil moisture level of the plants, to detect the root diseases that impact the plant growth directly. On the other hand, UGWSN is utilized in ground vegetation applications such as potato, peanuts etc. UGWSN is utilized in improving the natural resource and plays a role in nature conservation[3].

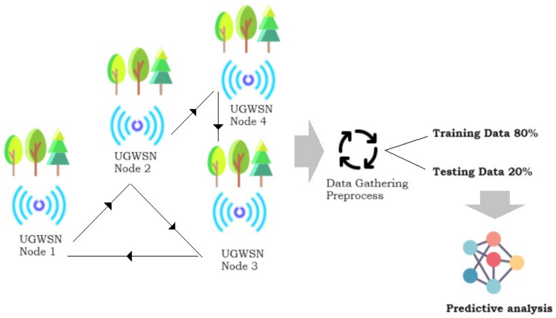

Fig 1. General structure of disaster analysis in Hill stations using UGWSN

Fig 1 shows the general structure of disaster analysis through UGWSN model in which various sensor nodes are placed in the underground[4], near the trees, buildings to extract the environmental data. Hill station disasters are such as flood, land slide and earth quakes. All these anomalies depend on the slope regions and its soil strength. In predictive analysis large amount of data is collected from hill regions in terms of soil strength, sudden vibration, water level increase etc. the general flow of prediction process is explored here. The utilization of UGWSN reduces the data overhead during emergency data alert. The location of the nodes is represented by unique identify numbers helpful to analyse the frequently occurring locations. The faster the data transmission then the analysis and alert is faster too[5].

The WSN modules are optimized to produce efficient data transmission with low data loss. The loss of data during critical conditions impacts the result of predictions. Power saving is one of the important criteria of the WSN systems. The battery backup maintenance, battery failure conditions are primary reasons for high data loss in sensitive regions.

- The proposed approach considers the energy efficiency as most important criteria and developed the AI-optimized neural computing for reroute planning. In the similar way, data loss rate plays a significant role and related to network performance.
- The key reason for data loss is due to loss of energy in the node, battery draining and short circuit. During such situations the UGWSN with AI-OPNC model optimize the failed route and make reestablishment of new route.

- The massive data collected from the nodes are secured in the cloud storage where predictive analysis is made. Keeping the historical parameters of the hill regions, the predictions are framed when meeting the similar situation.
- The alert is further uploaded in cloud for global accessibility and research. The proposed approach focused on optimization as well as predictive analysis.

The rest of the journal is formulated with existing articles study and ideas exploration in Section II, followed by the system design key considerations in Section III, the system implementation method, the process and the evaluation of various metrics are explored in section IV. The results obtained in the proposed design and its challenges are discussed in Section V.

2 Background Study

Sharma et al. (2021) the detailed study on role of internet of things in development of underground sensor network is discussed here. Disasters are of different types such as flood, earth quakes, landslides, forest fire etc. the study considers various critical factor behind the disaster detection and management system is explored here. The considerations given in the study is helpful to evaluate the requirements on disaster analysis system design. The major challenge in the presented methods is that comprehensive study is made, not analytical performance is compared here [6]

Radhakrishnan et al. (2022) The author presented a quality assured wireless network for underground communication network. Energy optimized hierarchal routing model is developed here with the packet delivery ration of 78.2%, throughput 83.5% etc. deep learning-based routing mechanism is created here. The challenges faced by the approach is that data over head need to be reduced [7].

Wang et al. (2019) the author presented a system that defines the underground sensor network through internet of things enabled geomagnetic algorithm. The presented concept is utilized in hill areas, mining etc. the variation of position in sensors depends on the underground changes are detected and monitored using the internet of things. The performance measure of the proposed model is evaluated in terms of accuracy. The system is utilized in emergency hedging. The presented system have the challenge of handling the sensor drop out analysis rate, as the sensors get damaged by the natural disasters, it need to be rerouted in a automated way [8].

Z.Duan et al. (2019) the author explored the underground wireless sensor network using multiple base station activated belt-area network. The system is developed with gradient descent location mapping algorithm. The comparison of conventional routing algorithm is compared with the proposed gradient method. The coverage is increased and node failure is reduced with the presented method. The drawback of the presented approach is handling the dynamic nodes in the network[9].

F. F. Hossain et al et al. (2022) the author discussed on real time embedded hardware enabled wireless sensor network using long range wireless area network represented as LoRaWAN. Based on the received signal strength (RSSI) values the system is focused with reducing the path loss in the network. The soil moisture level is detected through uncrewed aircraft system(UAS). The energy efficiency is evaluated comparing various state of art approach but still the drawback in the system is complex hardware's and its maintenance creates burdens[10].

- From the existing study, various challenges are explored in terms of underground wireless sensor network. The hierarchal routing model produces more data overhead even though the packet delivery ratio is good. The increasing overhead degrade the performance.
- Through LoRa the performance and real time update of data seems better but still the drawback in the system is complex hardware's and its maintenance which creates continuous monitoring and calibrations.

- Keeping various constrains as research gap in the presented study, the proposed system focused on creating a UGWSN model with Artificial intelligence enabled predictive analysis framework.
- The benefit of AI enabled system implemented here is that the reconfiguration and self-repairing made feasible, failure of sensor, failure of battery can be recovered through immediate support system created by predictive analysis model.

3 System Design

The energy efficiency is the primary need in wireless sensor network to sustain longevity and reliable operations in the network. The network is optimized to achieve energy efficiency and best computing performance. The proposed system is evaluated with the help of real time sensors such as vibration sensor and slope detection sensors data collectively gathered from Kaggle free data access portal. The predictive analysis is developed with the help of sensor data as well as dynamic test data provided.

4 Methodology

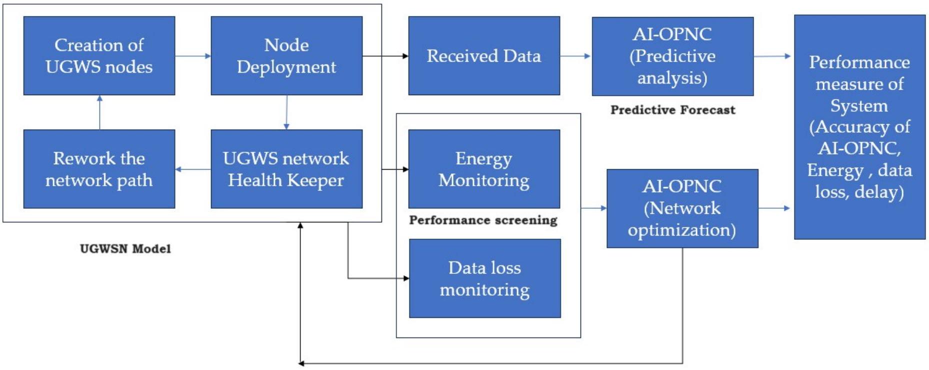

Fig 2. System architecture of proposed AI-OPNC model

Fig 2. Shows the system architecture of proposed AI-OPNC model in which the UGWSN network health monitoring as well as predictive analysis through received data on disaster management is focused.

Creation of UGWSN model

The Network consists of random UG nodes, deployed with random distance, random cost and random energy assigned at every iteration of the network. The sensor nodes are organized initially using shortest distance based sorting algorithm.

Design of Predictive analysis block

The AI-OPNC predictive analysis block, read the various data collected from sensors on hill stations. The data contains the positional changes of the slope area, soil strength and flow of sudden water etc. Here in the proposed system, the Kaggle dataset on land slide is considered. These datasets are ensembled to create a new dataset contains various information regarding the earth quake data, soil strength, slope changes collected during historical disaster situation.

The data is split into training data of 80% and testing data of 20% for AI-OPNC based anomaly prediction and self-analysis system. Based on the performance obtained over the pre-trained data the model is fixed into evaluation. The dynamic data or the part of training data is fetched as test data to analyse the performance of the proposed model in terms of accuracy and prediction quality. Using AI algorithm on predictive analysis and self-repairing (PASR) the forecast data is updated and alter mechanism is uploaded into the cloud.

Design of Network optimization block

The second phase of proposed model is the network optimization model in which the UGWSN health is keenly monitored in terms of energy efficiency and data loss. The proposed approach considers the energy productivity as most significant standards and fostered the man-made intelligence improved brain registering for reroute arranging. In the comparable manner, information misfortune rate assumes a huge part and connected with network execution. The critical justification behind information misfortune is because of loss of energy in the hub, battery depleting and impede. During such circumstances the UGWSN with artificial intelligence OPNC model improve the bombed course and make restoration of new course.

The Energy efficiency eqn.(1) of the UGWSN is measured as per the ratio of energy received at the outcome device with respect to the energy level initiated during the input end or the input energy. The loss of energy with various iteration (iteration=1000) are plotted in the results.

$$\text{Energy } \dot{\eta} = \sum \frac{Wout\_node}{Win\_node} \text{x}100 \qquad (1)$$

Where Wout_node is the energy received at the outcome device, Win_node is the energy level initiated. The utilization of AI-OPNC for self-repairing is happened in case of energy lost in the node. The self-repairing based routing is selected though the most recent best route acquired through sorting algorithm.

A. Algorithm : PASR

Predictive analysis and Self-repairing

```
Start
For i=1:number_of_iterations
D=inputrawdata
X=trainingdata
Y=testingdata
M=NeuralNetwork(X,Y)
T=dynamic test data
Mtest=NeuralNetwork(M,X,T)
[Tp,Tn,Fp,Fn]=Confusion(M)
Accuracy=Tp+Tn/Tp+Tn+Fp+Fn
New_model=PASR(Mtest_data)
End
```

B. Implementation Summary

PASR" (Predictive Analysis and Self-Repairing) in a pseudocode-like format is explored here, as Initialization:
Initialize the number of iterations for the algorithm.

Loop:
Iterate for a specified number of times, from 1 to number_of_iterations.

Data Preparation:
Load the input raw data D.

Split the data into training data X and testing data Y.

Neural Network Training:
Train a neural network model M using the training data X and testing data Y.

Dynamic Test Data:
Get dynamic test data T.
Neural Network Testing:
Use the trained model M to predict on the dynamic test data T, resulting in Mtest.

Confusion Matrix:
Calculate the confusion matrix metrics, including True Positives (Tp), True Negatives (Tn), False Positives (Fp), and False Negatives (Fn) based on the predictions from Mtest.

Accuracy Calculation:
Calculate the accuracy of the model using the confusion matrix values (Tp, Tn, Fp, Fn).

Self-Repairing Mechanism:
Apply some form of self-repairing or self-improvement to the model. It appears to create a "New_model" using Mtest_data, but the details of how this self-repairing process works are not specified in the provided pseudocode.

End of Loop.

The pseudocode outlines a basic structure of an iterative process for predictive modeling and self-repairing using a neural network.

5 Results and Discussions

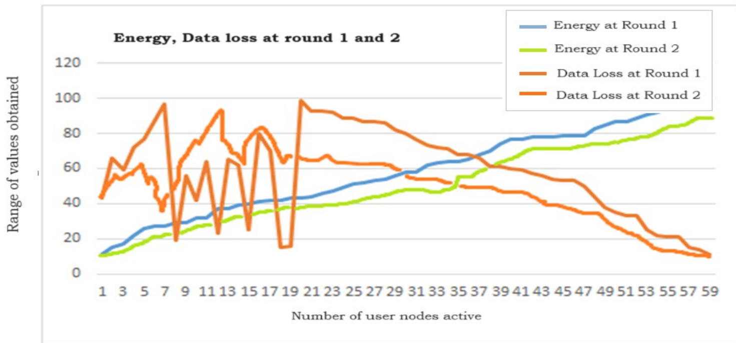

Fig 3. Energy efficiency and Data loss of AI_OPNC model

Fig 3. Shows the relationship between the energy efficiency obtained at various levels of node establishments and iterations monitored with the AI-OPNC model. The graph depicts that energy level increases and maintained with respect to the data loss rate degraded.

Table 1. Accuracy of AI-OPNC model.

AI-OPNC Iterations	Accuracy on Model fitting	Accuracy on dynamic input
10	45	55
50	57	56
100	59	65
150	65	68
200	75	69
300	78	75
400	86	78
450	85	89
500	74	86
600	89	84
700	90	95
1000	95	96

Table 1 shows the various recordings of accuracy on fitting stage and dynamic testing stage.

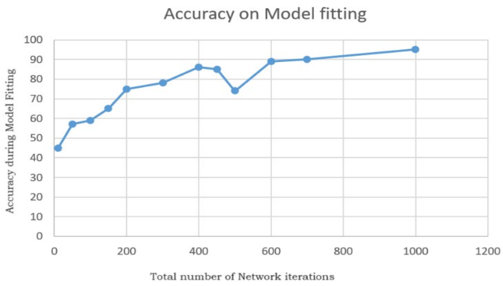

Fig 4. Accuracy of prediction at Model fitting

Fig 4. Shows the predictive analysis result in terms of accuracy, where the number of node establishment at round 1 to 1000 increases different levels of predictions are obtained. With limited number of data obtained at stage 100 say example the accuracy level available in the range of 70%, as the node communication established with increased iterations, the learning pattern available for the AI-OPNC increases hence the accuracy of prediction increases.

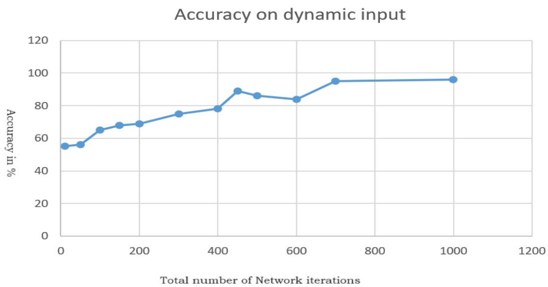

Fig 5. Accuracy of prediction on dynamic testing

Fig 5. Shows the prediction analysis bring about terms of dynamic testing, where the quantity of node establishment at cycle 1 to 1000 increments various degrees of expectations are acquired. With set number of information acquired at stage 100 say model the exactness level accessible in the scope of 65%, as the node correspondence laid out with expanded cycles, the learning design accessible for the artificial intelligence OPNC increments subsequently the precision of expectation increments.

Table 2. Comparison of existing state of art approach with proposed model

Reference	Methodology	Statistical metrics
[2]	LoRa , Zigbee based Multi-level WSN	Path loss @868Mhz Min=55, Max=72 @2.4Ghz Min=68, Max=76
[3]	CSMA based Magneto-inductive WSN	60uAmps - Sleep mode, 253mAmps in transmit mode, 0.49mAmps in receive mode
[7]	Energy hirerichal optimized routing/ deep learning	Energy utilization 89.71%, Packet delivery ratio 78.2%, Average packet delay 82.3%, Throughput 83.5%, Packet loss 91%
Proposed method	AI-optimized predictive analysis	Packet delivery ratio=99%, Packet loss=1%, Throughput 95%, Energy utilization 90%

Table 2. shows the comparison of various parameters on underground wireless sensor network towards achieving the effective communication, [2] the path loss evaluation is compared, in [3] the multi-mode operation of UGWSN is evaluated. In [7], Energy utilization is focused and achieved 89.71%, packet delivery ratio is 78.2%, Throughput is 83.5%, Packet loss is 91%, Packet delay is 82.3% is achieved. Similarly with AI-OPNC model the packet delivery ratio is 99%, packet loss is 1% from the whole data transit, throughput is 95% and energy utilization is 90%.

- The major challenge of proposed approach is that the performance purely depends on the learning input and quality provided from the network.
- The anomalies of uncertainty need to be filtered out in future implementations.

6 Conclusion

The arising development of remote sensor organizations (WSN) frameworks gives different advantages over the information transmission at various conditions. Remote observing frameworks are mean a lot to make persistent assessment of conditions, medical services, security, crisis reaction and shrewd analysis. Underground remote sensor organizations (UGWSN) are expanding in late developments for identification of different crisis condition and to give early aware of the people groups. Despite the fact that UGWSN models face different difficulties as far as establishments and upkeep, progressively evolving climate, sensor life length impacted by climate, commotion and so on, power limitations go about as significant issue in having maintainability. The proposed approach considers an energy productive underground remote sensor organization (UGWSN) utilizing computer based intelligence advanced prescient brain registering (artificial intelligence OPNC) models early location and analysis of calamities leads in slope locales. The essential objective upheld on location of catastrophe triggers, for example, earth shudders, land slide elements and to investigate the event stamps utilizing man-made intelligence OPNC model, then again the organization wellbeing is checked through network wellbeing attendant. The proposed framework execution is measure in two progressively eases, for example, network execution as far as energy proficiency, information misfortune and so on and the presentation of computer based intelligence OPNC with regards to prescient analysis through precision. The proposed framework accomplished 96% accuracy, energy proficiency increments 10% concerning information misfortune smothered 8% utilizing UGWSN nodes.

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