

# Rule Based Collector Station Selection Scheme for Lossless Data Transmission in Underground Sensor Networks

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**Abstract:** There are fundamentally two different communication media in wireless underground sensor networks. The first of these is a solid medium where the sensor nodes are buried underground and wirelessly transmit data from underground to aboveground. The second is an underground medium such as tunnel, cave etc. and the data is transmitted from underground to the aboveground through partially solid medium. The quality of communication is greatly influenced by the humidity of the soil in both environments. The placement of wireless underground sensor nodes at hard-to-reach locations makes energy efficient work compulsory. In this paper, rule based collector station selection scheme is proposed for lossless data transmission in underground sensor networks. In order for sensor nodes to transmit energy-efficient lossless data, rule-based selection operations are carried out with the help of fuzzy logic. The proposed wireless underground sensor network is simulated using Riverbed software, and fuzzy logic-based selection scheme is implemented utilizing Matlab software. In order to evaluate the performance of the sensor network; the parameters of delay, throughput and energy consumption are investigated. Examining performance

evaluation results, it is seen that average delay and maximum throughput are accomplished in the proposed underground sensor network. Under these conditions, it has been shown that the most appropriate collector station selection decision is made with the aim of minimizing energy consumption.

**Keywords:** sensor network; fuzzy; rule based; underground; collector station

## I. INTRODUCTION

Along with the recent developments in communication techniques, sensor network applications in underground environment have increased significantly. Wireless underground sensor networks is a promising field of work that is composed of underground wireless sensors. It provides many applications that are not possible with wired underground monitoring techniques. Subject area of wireless underground sensor network covers landslide forecast, border patrol, security, underground infrastructure monitoring, soil condition monitoring, earthquake prediction, and etc. However, the most challenging part of underground communication is the propagation environment that is a solid medium. The main reason

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for this is the diffusion environment is a solid medium, i.e., soil; unlike terrestrial wireless sensor networks where the propagation medium is air. Since conventional techniques of terrestrial wireless sensor network do not work well in underground soil environment, new approaches are needed.

Because sensor nodes have very limited radio power, it is important to reduce energy consumption in any wireless sensor network type. In the literature, a lot of research has been done on this subject. However, most of these investigations have been carried out mainly for terrestrial wireless sensor networks where the spreading environment is air. However, the underground environment is completely different from the terrestrial environment because the propagation medium is not the air, but the soil, a solid medium. Attenuation and path loss values are very high in the underground environment compared with the aboveground environment. Therefore, it is of great importance to investigate and find ways to reduce energy consumption in underground communications. In this way, it may be possible to increase the lifetime of wireless underground sensor networks. In addition, the reliability of data is another important feature that requires attention in underground communication. It is because the bit error rate is different from aboveground communication. Nowadays, there are several studies investigating the use of underground error control code for increasing the reliability of wireless sensor networks. Nevertheless, there are a limited number of works to reduce the energy consumption of wireless underground sensor networks.

In this paper, rule based collector station selection scheme is proposed for lossless data transmission in underground sensor networks. Rule-based selection operations are implemented with the help of fuzzy logic. Riverbed modeler is used for simulation model and Matlab software is used for fuzzy logic-based selection scheme. The parameters of delay, throughput and energy consumption are investigated. Considering performance evaluation

results, it is shown that the most appropriate collector station selection is made and energy consumption is minimized.

## II. RELATED WORKS

In the literature, there are many studies on wireless underground sensor networks. Recent studies have focused on energy efficiency and collector station selection techniques.

Ichihashi et al. reported a paper on the new camera based system called ParkLotD for detecting vacancy/occupancy in parking lots [1]. Lokshina and Insinga discussed a decision support system based on fuzzy methods that are applied to the interpretation and processing of gas-dynamic images received during monitoring and control processes of underground coal mine atmospheres [2]. Fischer et al. presented some of the issues that must be dealt with during the implementation of an oil leak detector in underground power cables [3]. Xianmin and Lan proposed a novel coal real-time monitoring system for the electrical haulage coal shearer that is based on multi-sensor data fusion theory [4]. Ichihashi et al. reported a paper on the performance of the detector based on the fuzzy c-means clustering and the hyper parameter tuning by particle swarm optimization [5]. Gauss and Bay presented an unsupervised fuzzy logic algorithm that can determine a trajectory for a subsurface planetary exploration robot through unknown environments, even in the presence of imprecise sensor data [6]. Ahmad et al. proposed an agent-based personal monitoring system using type-2 fuzzy to simulate the monitoring process for workers at time of hazard operation [7]. Zyada et al. presented a sensor fusion based fuzzy rules for humanitarian demining [8].

Fengying designed a new kind of wireless monitoring system in view of the shortcoming of traditional underground gas monitoring system [9]. Jaryani et al. presented a smart move algorithm for mobile sinks to improve routing operations and to increase the efficiency of wireless sensor network [10]. Sinha et al. pro-

posed a recognition and classification of pipe cracks using image analysis and neuro-fuzzy algorithm [11]. Sinha and Karray proposed a recognition and classification of pipe cracks using images analysis and neuro-fuzzy algorithm [12]. Gupta et al. presented a paper titled quantification of human error rate in underground coal mines—a fuzzy mapping and rough set based approach [13]. Fu et al. investigated a hesitant fuzzy linguistic gained and lost dominance score method [14]. Ye et al. presented a simplified single wheel model for underground mining electric vehicles with bounds of system uncertainties [15]. Zhou et al. proposed an analytic hierarchy process and fuzzy comprehensive evaluation method to construct the comprehensive evaluation index system of the multiple constraint factors of city underground space development and utilization [16]. Ye et al. presented the modeling of an underground mining electrical vehicle for acceleration, braking and speed maintenance with a global fuzzy model [17].

Klomjit and Ngaopitakkul presented the proper input pattern of fuzzy logic algorithm for fault type classification in underground cable [18]. Liu et al. applied the grey system theory in order to solve the problem of underground engineering reinforcement and reconstruction, on the basis of the thought of system and fuzzy decision, and built index system of underground engineering reinforcement and reconstruction [19]. Cai et al. proposed a miner fuzzy detection method based on mixture Gaussian model in order to monitor the dangerous areas in the underground coal mine automatically [20]. Moshtagh and Aggarwal presented the results of investigations into a new fault location technique using advanced signal processing technique based on wavelet technology to extract useful information [21]. Ma and Ma presented a gas disaster collaborative monitoring system in order for gas monitoring system to increase precision and real-time capacity [22]. Chaki and Chattopadhyay described a practical and reliable solution/approach to achieve a semi-automated sewer pipeline inspection [23]. Guoliang and Sijing

considered the safe indicator that is separately based on the perspective of corporate social responsibility in order to make the selection of mining method more scientific and rational [24]. Zhang et al. investigated the five kinds of underground space, including commercial, culture and entertainment, fitness, hotel, dining and garage [25].

Li et al. attempted to provide a comprehensive and in-depth survey of the existing research on underwater magnetic induction communications, classified as the four topics of channel modeling, reliability guarantee, range extension, and capacity enhancement, and present the state-of-the-art advances on each topic [26]. Li et al. investigated two fundamental problems that under which conditions a relay should be deployed and where to deploy it if necessary in terms of the energy and delay performance in linear underwater acoustic networks [27]. Tan et al. designed and implemented a test bed of several magnetic induction based communication systems in an in-lab underground environment [28].

Kisseleff et al. developed channel and noise models for magneto inductive wireless underground sensor networks using magneto inductive waveguides [29]. Kunnath and Warriar discussed underground channel characteristics and derived a path loss model for the underground communication [30]. Xiaoya et al. developed improved channel models based on time-domain in order to characterize underground-underground, underground-aboveground and aboveground-underground electromagnetic waves channels, which capture the effects of environment parameters such as soil composition and soil moisture, and system parameters such as the antenna gain, operating frequency, the sensor burial depth [31].

In above mentioned papers; gas leakage system, oil leak detection system, subsurface exploration robot, mine detection system, underground pipe crack classification system, motion of underground mining electrical vehicles, underground cable system and crack detection system of underground sewer pipelines are basically proposed for underground sensor

networks. Fuzzy logic approach is used for various purposes in those underground sensor networks. However; effect of soil humidity for buried sensor nodes, maximum depth of 4 meters solid communication medium and fuzzy input parameters of depth-energy-density together are not considered in above referenced works.

In this paper; soil humidity effect for sensor nodes, communication in solid medium up to 4 meters depth and fuzzy logic approach with input parameters of depth-energy-density are considered. The best collector station selection is accomplished with the proposed scheme.

Main contributions of this paper are as following:(i) Fuzzy logic based collector station selection scheme for wireless underground sensor network is proposed.(ii) Energy consumption is decreased with the help of loss-less data transmission.(iii) Design of wireless underground sensor nodes and network environment is simulated with Riverbed software. (iv) Outstanding increase in network performance is obtained compared to other schemes. (v) Analytical results obtained from Matlab software [32] are confirmed with simulation results acquired from Riverbed software [33]. (vi) Proposed fuzzy logic based approach is designed and simulated using Riverbed software and Matlab software together in wireless underground sensor networks for the first time in the literature.

### III. WIRELESS UNDERGROUND SENSOR NETWORKS

Wireless underground sensor networks have recently been the subject of research for earth monitoring [7]. These networks consist of subterranean sensor nodes that track soil conditions and aboveground access points that are wirelessly connected to the underground nodes to transmit data to end users [12]. Wireless underground sensor networks can provide efficient and precise information on a few conditions such as soil moisture with less cost compared to satellite and aerial remote sensing [18].

#### 3.1 Application area of wireless underground sensor networks

Agriculture is one of the most promising areas for wireless underground sensor networks [23]. Sensor nodes in agriculture can be used to monitor soil parameters such as water content, mineral content, salinity and temperature; then transmit these values to a control station in real time [4]. In addition, irrigation control mechanisms can be applied to assist in the maintenance of sports fields such as golf courses [9].

Security is an area that can be used for the deployment of underground networks due to the concealment of nodes [2]. The sensor nodes can be embedded in a shallow depth to detect motion on the surface [11]. This scenario is useful for home security as well as military applications such as border patrols [15].

Infrastructure monitoring is another possible application scenario for wireless underground networks [10]. For example, wireless underground sensor networks can be used to monitor pipelines and detect leaks [6]. To achieve this, different processes can be applied such as the use of sensor nodes inside or outside the pipeline [22].

#### 3.2 Communication methods in wireless underground sensor networks

Underground communication is sensitive to changes in environment such as increase or decrease in soil moisture in contrast to air communication [23]. For this reason, network topology and connection status can change dynamically over time depending on soil moisture level [8]. An underground node is considered to be connected to the network if it can connect with a fixed or moving underground node at multiple hops at any time interval [13]. In this way, the underground sensor node can transmit its data over the nearby nodes to the access point [4].

Network topology consists of two different types of nodes for a wireless underground sensor network;(i) underground sensor nodes

buried underground surface,(ii) aboveground sensor nodes that are responsible for collecting data coming from underground sensor nodes [9]. There are three different communication channels based on the location of recipients and transmitters for node communications;(i) underground–underground,(ii) aboveground–underground,(iii) underground – aboveground [18].

#### IV. PROPOSED FUZZY LOGIC BASED APPROACH

In this study, network design where underground-underground communication is made among underground sensor nodes that are not possible to be re-energized due to their sub-soil location; and underground-aboveground communication is carried out with collector stations were investigated. The underground sensor nodes transmit their data to the collec-

tor station nearest to them. If it is not possible to transfer data directly to the collector station, they transmit their data in an ad-hoc manner via other underground sensor nodes to the collector station.

Figure 1 shows the wireless underground sensor nodes and collector stations in the proposed underground sensor network. The task of underground sensor nodes is to sense data. The underground sensors nodes that is close to surface transfer data from the deep underground sensor nodes to the collector stations in addition to data sensing. Collector station is used to collect data, and collected data can be monitored from any online device. The underground sensor nodes provide the lowest possible energy consumption by waiting in sleep mode for the idle times. Underground sensor nodes are placed to the depth of maximum 4 meters. Because possibility of healthy communication decreases after 5 meters, depth of 4 meters is chosen as maximum in the simulation model.

Table 1 shows the simulation parameters and values of the underground sensor network. Data rate is 10 kbps, and modulation scheme is bpsk. Number of sensor node and collector station are 32 and 6, correspondingly. Transmitter power is 800 mw that is chosen taking sensor node having maximum depth into account. Size of data packet is 40 byte. Frequency is set to 350 MHz that is suitable for underground communication.

The procedure of the proposed collector station selection scheme is as following:(i) Wireless underground sensor nodes sense data from the underground environment.(ii) Collector station selection scheme is employed for choosing the best collector station.(iii) Utilizing depth-energy-density as input parameters, closeness of collector station is decided as an output parameter.(iv) The best collector station selection decision is made according to input parameters.(iv) Sensed data is transmitted to the selected collector station.(v) If direct communication to any collector station is not possible, data is transmitted in an ad-hoc manner with the help of sensor nodes close to surface.

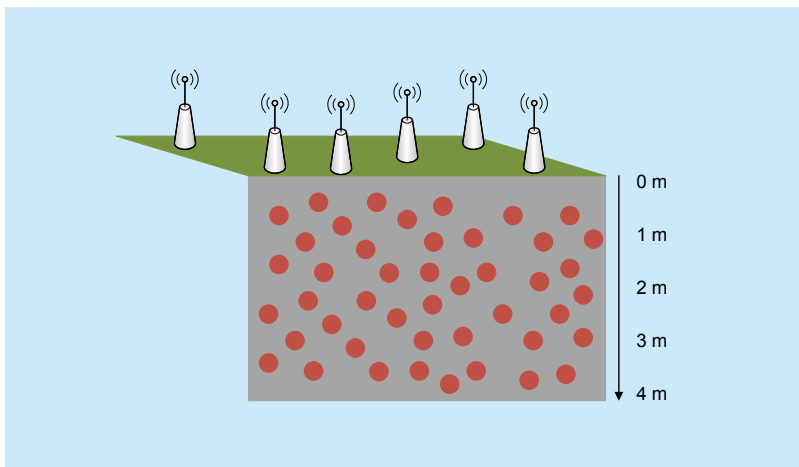


Fig. 1. Wireless underground network environment.

Table I. Simulation parameters and values.

Simulation Scenario	Related Parameters and Values	
	Parameter	Value
	Data rate	10 kbps
	Modulation	bpsk
	Number of sensor node	32
	Number of collector station	6
	Transmitter power	800 mw
	Size of data packet	40 byte
	Frequency	350 MHz
	Maximum depth	4 m



Fuzzy logic is an artificial intelligence method used for applications requiring advanced technology in areas such as engineering, economics, medicine, etc. The fuzzy logic aims to make specific decisions from the approximate information, similar to the ability of human decision.

In figure 2, a block diagram of the proposed underground fuzzy logic system is given. Fuzzy logic system composes of fuzzifier, inference engine and defuzzifier. Fuzzifier converts a clear input to a fuzzy value while defuzzifier converts the set of output values into a single point wise value. These three units are constantly in communication with the information base of the rule base and membership functions. In the fuzzifier unit, certain values are converted into fuzzy data sets. After these fuzzy sets are processed in the inference engine, the defuzzifier unit converts them into numerical values. After the defuzzifier unit, there is stage of decision table. Output value of collector station selection is obtained using three input values of depth, energy and density. There are three input parameters for membership functions and three levels for these membership functions.

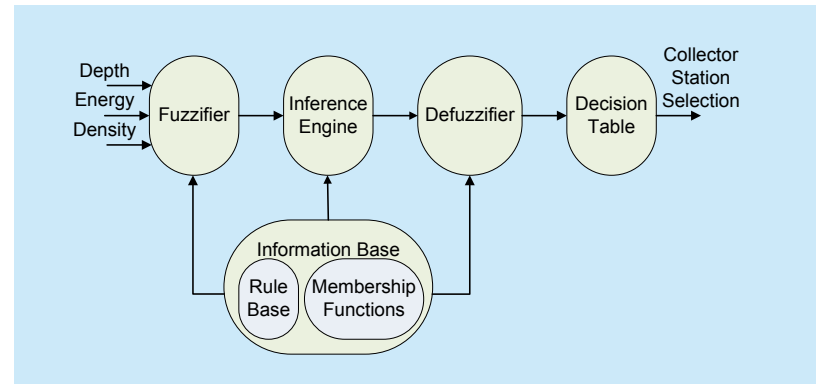
In figure 3, membership functions for depth of an underground sensor node are demonstrated. Depth of sensor nodes changes between 0 meter and 4 meters. There are three levels namely; low, medium and high. Depth is the most effective parameter for the collector station selection.

In figure 4, membership functions for residual energy of an underground sensor node are demonstrated. Residual energy of sensor nodes changes between 0 joule and 8 joules. There are three levels namely; low, medium and high.

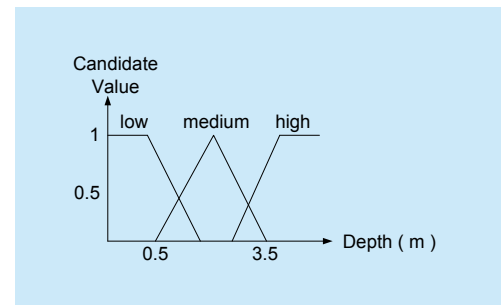
In figure 5, membership functions for density of an underground sensor node are demonstrated. Density of sensor is described as sensed data traffic of an underground sensor node. Density of sensor nodes changes between 0 % and 100 %. There are three levels namely; low, medium and high.

Table 2 gives sample rules from the fuzzy

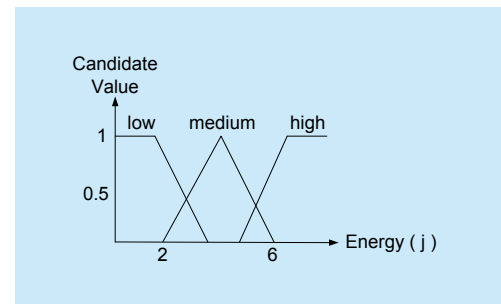
rule table that is composed of totally twenty seven rules. These rules are utilized to



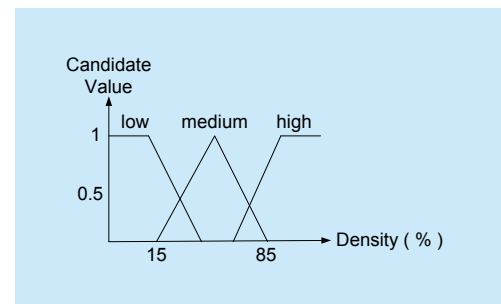
**Fig. 2.** Block diagram of the proposed underground network.



**Fig. 3.** Membership functions for depth of an underground sensor node.



**Fig. 4.** Membership functions for residual energy of an underground sensor node.



**Fig. 5.** Membership functions for data density of an underground sensor node.

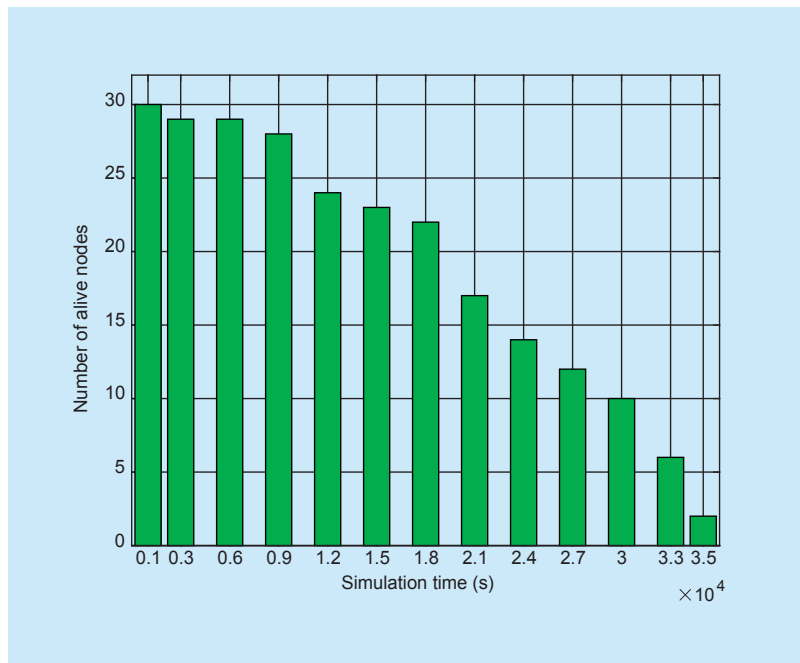
determine the collector station selection of the wireless underground sensor nodes. For example; if depth of sensor node is medium, residual energy of sensor node is high, and data traffic density of sensor node is high, then very close collector station is selected.

**Table II.** Samples from rule table.

Rule Table	Sample Rules	
	If (depth is high) and (energy is low) and (density is medium) then	(collector station selection is very close)
	If (depth is low) and (energy is medium) and (density is low) then	(collector station selection is close)
	If (depth is medium) and (energy is high) and (density is high) then	(collector station selection is very close)
	If (depth is low) and (energy is low) and (density is medium) then	(collector station selection is close)
	If (depth is high) and (energy is low) and (density is high) then	(collector station selection is very close)

**Table III.** Samples from fuzzy system results.

Fuzzy System Results	Sample Results			
	Depth ( m )	Energy ( j )	Density (%)	Collector Station Selection
	3.2	1.8	58	very close
	0.4	1.7	47	close
	2.2	6.4	88	very close



**Fig. 6.** Lifetime of sensor nodes according to simulation time.

## V. PERFORMANCE ANALYSIS OF GRAPHICAL RESULTS

In order to evaluate the performance of the proposed underground wireless sensor network; throughput, average delay, residual energy, path loss, packet loss ratio and node lifetime parameters are investigated.

Table 3 shows examples of values obtained from proposed underground sensor network fuzzy system results. Accordingly, performance evaluation of collector station selection approach is examined as a result of fuzzy logic system.

In figure 6, lifetime of sensor nodes according to simulation time is demonstrated. Number of sensor nodes slightly decreases through simulation time as energy of sensor node reduces. When all the energy of a sensor node finishes, the sensor node is defined as dead sensor node.

In figure 7, overall network throughput according to simulation time is demonstrated. With the help of perfect collector station selection scheme, lossless data transmission is guaranteed. By means of lossless data transmission, throughput remains above 96 % for the first half of simulation time. For the second half of the simulation time throughput slightly decreases because of dead sensor nodes.

In figure 8, residual energy results according to average delay for the sensor nodes exist in the depth of 1 meter are illustrated. For six different collector stations, residual energy changes between 0J to 6J while average delay changes between 0ms to 85ms. As residual energy decreases up to 3 J, average delay increases through simulation time where sensor nodes are at depth of 1 meter. Once residual energy decreases under 3J, average delay stays steady between 68ms and 85ms according to different collector stations.

In figure 9, residual energy results according to average delay for the sensor nodes exist in the depth of 2 meters are illustrated. For six different collector stations, residual energy changes between 0J to 6J while average delay changes between 0ms to 104ms. As residual

energy decreases up to 3 J, average delay increases through simulation time where sensor nodes are at depth of 2 meters. Once residual energy decreases under 3J, average delay stays steady between 87ms and 104ms according to different collector stations.

In figure 10, residual energy results according to average delay for the sensor nodes exist in the depth of 3 meters are illustrated. For six different collector stations, residual energy

changes between 0J to 6J while average delay changes between 0ms to 126ms. As residual energy decreases up to 3 J, average delay increases through simulation time where sensor nodes are at depth of 3 meters. Once residual energy decreases under 3J, average delay stays steady between 105ms and 126ms according to different collector stations.

In figure 11, residual energy results according to average delay for the sensor nodes exist

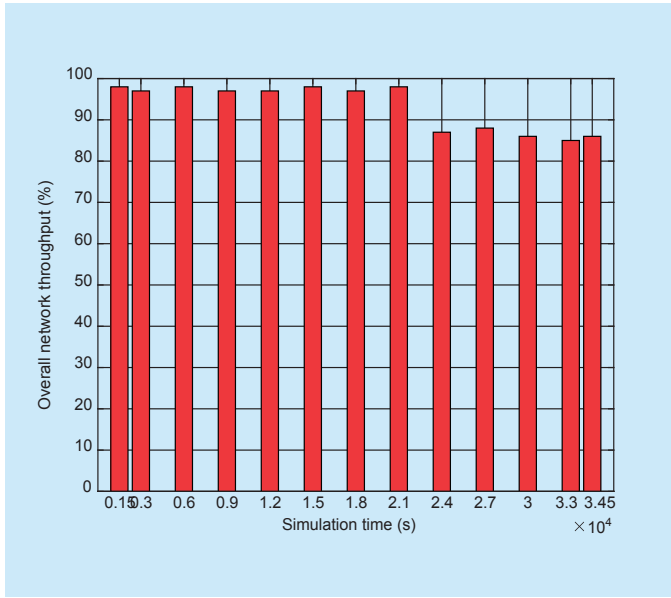


Fig. 7. Overall network throughput according to simulation time.

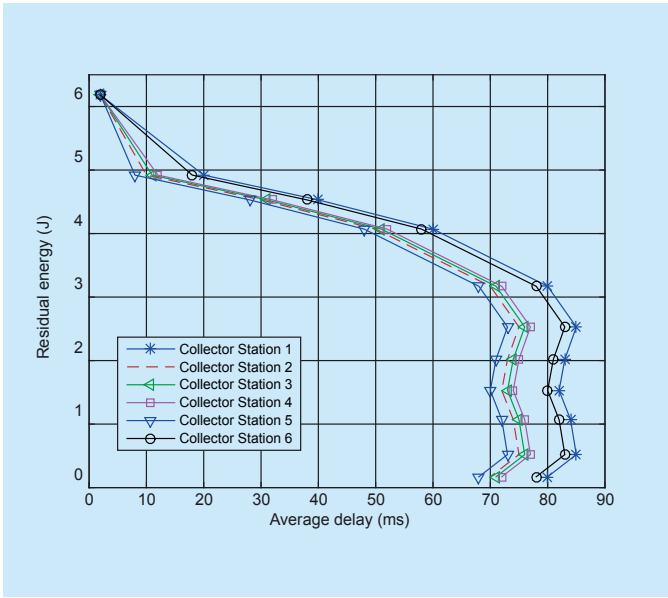


Fig. 8. Residual energy results according to average delay for the depth of 1 meter.

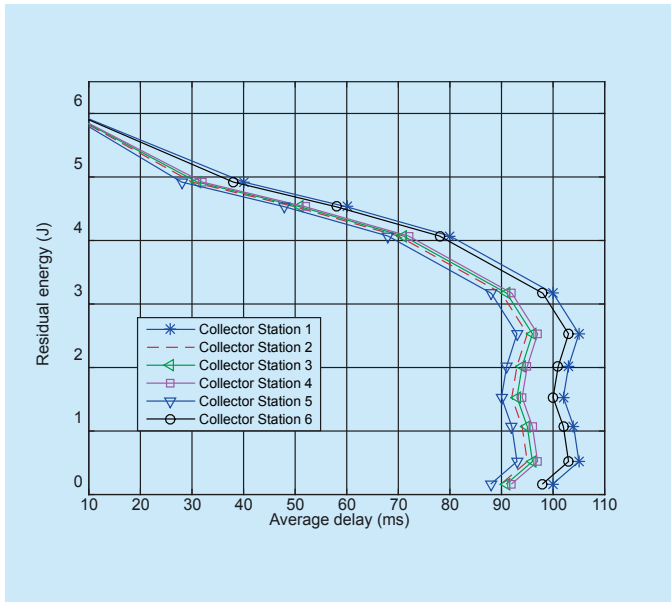


Fig. 9. Residual energy results according to average delay for the depth of 2 meters.

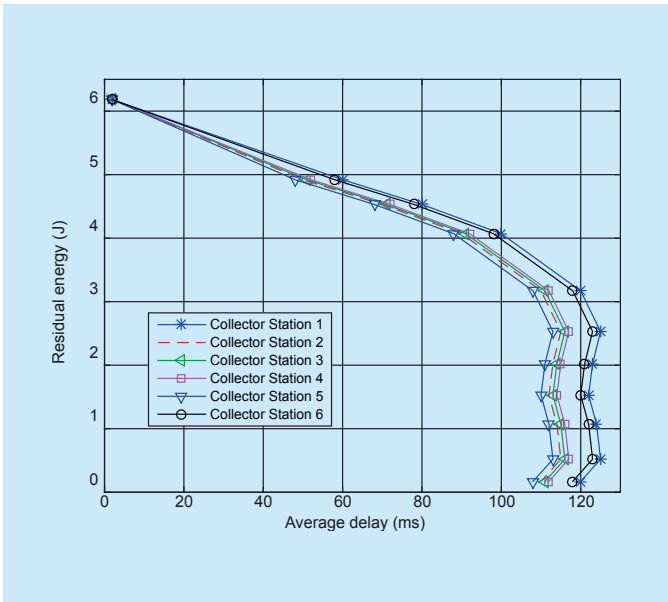


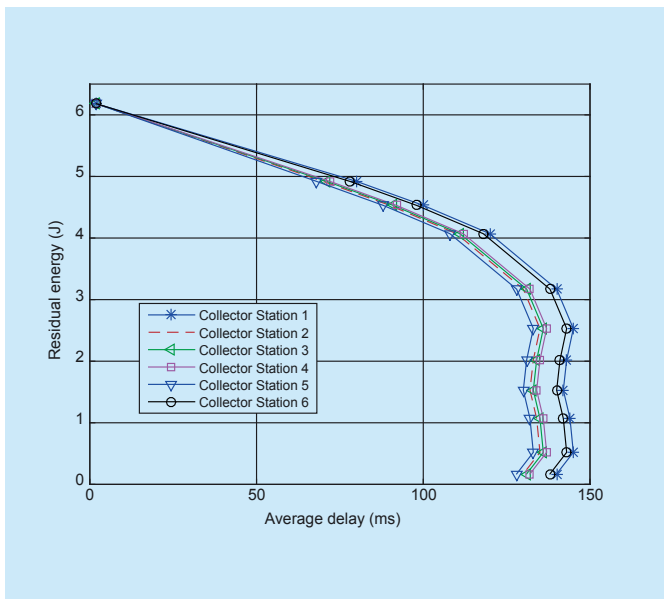
Fig. 10. Residual energy results according to average delay for the depth of 3 meters.



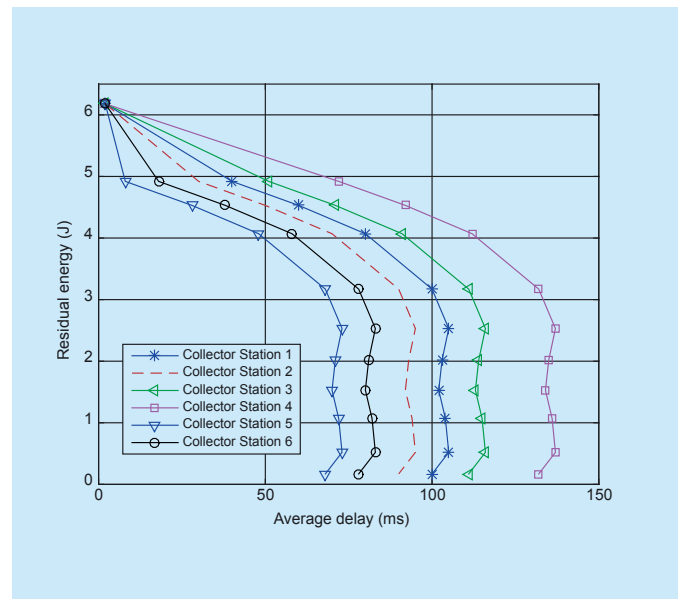
in the depth of 4 meters are illustrated. For six different collector stations, residual energy changes between 0J to 6J while average delay changes between 0ms to 144ms. As residual energy decreases up to 3 J, average delay increases through simulation time where sensor nodes are at depth of 4 meters. Once residual energy decreases under 3J, average delay stays steady between 130ms and 144ms according

to different collector stations.

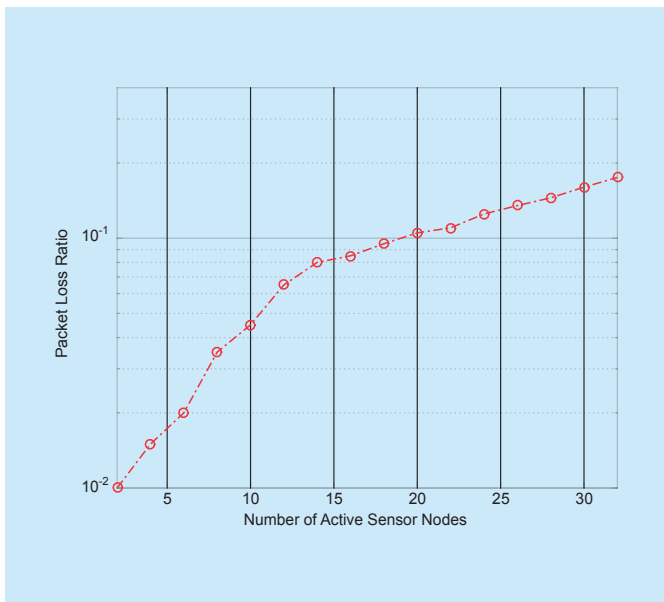
In figure 12, residual energy results according to average delay for the sensor nodes exist in the random depth are illustrated. For six different collector stations, residual energy changes between 0J to 6J while average delay changes between 0ms to 145ms. As residual energy decreases up to 3 J, average delay increases through simulation time where sensor



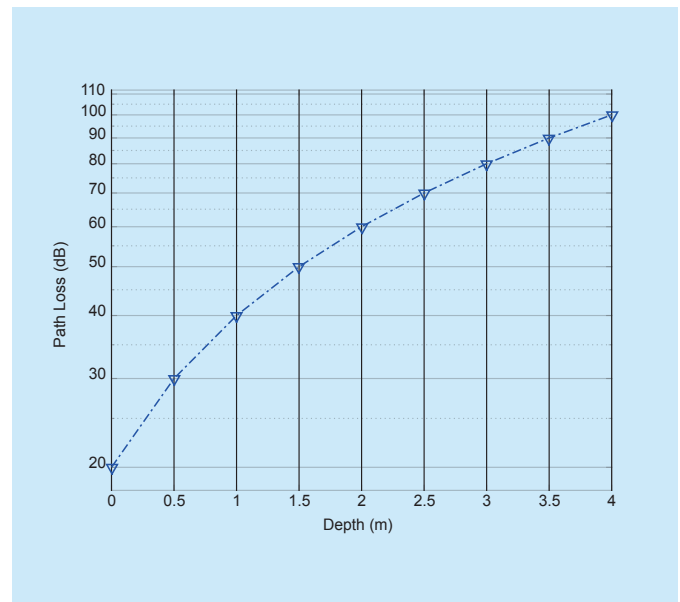
**Fig. 11.** Residual energy results according to average delay for the depth of 4 meters.



**Fig. 12.** Residual energy results according to average delay for the random depth.



**Fig. 13.** Packet loss ratio results according to number of active sensor nodes at random depth.



**Fig. 14.** Path loss results according to depth.

nodes are at random depths. Once residual energy decreases under 3J, average delay stays steady between 65ms and 145ms according to different collector stations.

In figure 13, packet loss ratio results according to number of active sensor nodes at random depth are demonstrated. As number of active sensor nodes increase, packet loss ratio increases where soil humidity rate is taken as 0%.

In figure 14, path loss results according to depth are illustrated. Depth of sensor nodes changes between 0m and 4m. Path loss changes between 20dB and 100dB. Path loss increases as depth of sensor node increase. Soil humidity rate is taken as 0% for this scenario.

In figure 15, path loss results according to soil moisture at depth of 2m are illustrated. Soil moisture changes between 0% and 100%. Path loss changes between 60dB and 80dB.

In this work, the proposed fuzzy logic based scheme is compared with two different schemes, namely, simple additive weighting [34] and fuzzy simple additive weighting [35]. In Table 4, performance comparison with related schemes is given. It is clearly seen that the proposed fuzzy logic based scheme has better performance than other schemes in terms of selection accuracy and energy saving.

## VI. CONCLUSION

Rule based collector station selection scheme for lossless data transmission for underground sensor networks is proposed in this paper. Rule-based selection operations are carried out utilizing fuzzy logic system for energy-efficient lossless data transmission of sensor nodes. Riverbed modeler software is used for simulation model of proposed sensor network environment and Matlab software is utilized for fuzzy logic-based selection process. Delay, throughput and energy consumption parameters are taken into account for performance evaluation of the proposed sensor network. When the performance evaluation results are examined, it is understood that the average delay and maximum throughput is achieved by

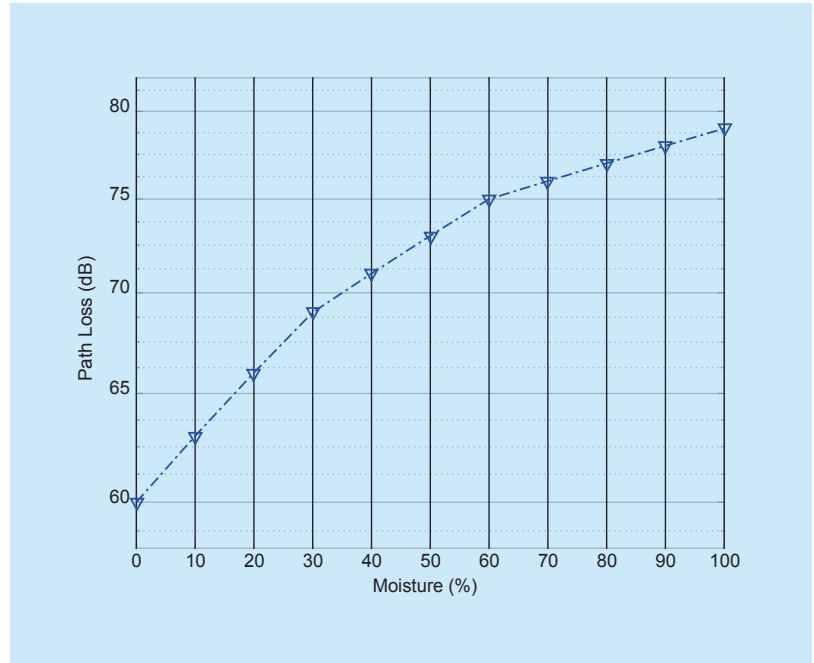


Fig. 15. Path loss results according to soil moisture at depth of 2m.

Table IV. Performance comparison.

	The proposed fuzzy logic based scheme	Simple additive weighting scheme	Fuzzy simple additive weighting scheme	Without any scheme
Selection accuracy	91%	83%	87%	-
Energy saving	79%	71%	75%	67%

means of proposed sensor network. It has been shown that not only the most appropriate collector station selection is made but also energy consumption is minimized with the proposed scheme.

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