### Fuzzy Rule-Based System for Route Selection in WSN Using Quadratic Programming



#### Manoj Kumar Mandal, Arun Prasad Burnwal, B. K. Mahatha, Abhishek Kumar, Santosh Kumar Das, and Joydev Ghosh

Abstract Wireless sensor network (WSN) is a part of wireless network which has flexible and dynamic nature in context of real-life applications. It has several usages in terms of user requirements. It consists of several nodes having limited energy capacity. Energy capacity of the nodes does not completely fulfil the requirement of the services. During transaction or transmission, data is dropped and fails to reach the destination node or base station (BS). This BS also suffers several types of difficulties for sending or receiving data packets. So, there is need of some techniques or modelling that help to protect this issue. Apart from energy, distance is also one important parameter for transmitting data successfully. Although energy is the crucial parameter, but, combination of both energy and distance plays an important role for managing efficient route of the network. The proposed method is the combination of intelligent technique as well as mathematical modelling that uses fuzzy logic as an intelligent technique and quadratic programming as a mathematical modelling for solving the proposed goal. The combination of both provides a robustness technique that uses two basic parameters, energy and distance, for selecting optimal route of

M. K. Mandal (🖂)

Department of Mathematics, Jharkhand Rai University, Ranchi 835222, India

A. P. Burnwal Department of Mathematics, GGSESTC, Bokaro, Jharkhand 827013, India

B. K. Mahatha Amity School of Engineering and Technology, Amity University Jharkhand, Ranchi 834001, India

A. Kumar

Department of Electronics and Communication Engineering, Swami Vivekananda Subharti University, Meerut 250005, India

S. K. Das

Department of Computer Science and Engineering, Sarala Birla University, P.O.-Mahilong Purulia Road, Birla Knowledge City, Ranchi, Jharkhand, India

J. Ghosh

School of Computer Science and Robotics, National Research Tomsk Polytechnic University (TPU), Tomsk, Russia

© The Author(s), under exclusive license to Springer Nature Singapore Pte Ltd. 2021 S. K. Das et al. (eds.), *Architectural Wireless Networks Solutions and Security Issues*, Lecture Notes in Networks and Systems 196, https://doi.org/10.1007/978-981-16-0386-0\_6 the WSN. The proposed method is validated in LINGO optimization software for formulating and validating the model efficiently.

**Keywords** Wireless sensor network · Quadratic programming · Fuzzy logic · Rule-based system · Routing

#### 1 Introduction

Wireless sensor network (WSN) is a part of wireless network which is also known as subset of a wireless network. In [1], there are several frameworks discussed in terms of optimization, localization, troubleshooting, and security analysis. This design frameworks influence several variations of the wireless network based on applications. WSN is one of the variations that influences rapidly for solving different issues and problem. In [2–4], several works are proposed for WSN based on nature-inspired techniques or algorithms. Figure 1 shows an illustration of WSN communication between multiple users that consist of several types of sensor nodes, base station

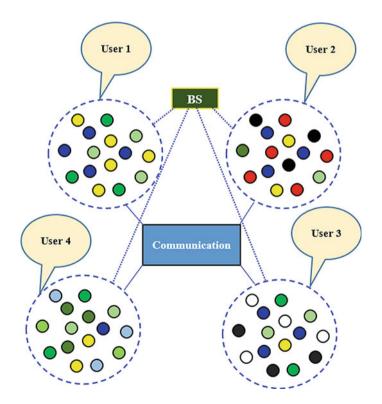


Fig. 1 Wireless sensor network communication between multiple users

(BS), and users. The purpose of these entities is to establish an efficient communication. Wireless sensor nodes are used to sense environmental information and send it to the BS for future references. BS previously stores the user queries in its database, receives sensed information from the sensor nodes, analyses it based on received user queries, and provides responses to the users. In this diagram, there are four users present to establish communication, but in real life, the number of users is more based on number of sensors used in the operational region. In this figure, variation of sensor nodes is more, because battery capacity of each sensor node is different as "Low", "Medium", "Poor", "Bad", "High", "Very High", "Sufficient", etc. These terms are known as linguistic variables in which assumptions are changed based on user or administrator.

The above-mentioned figure is one example, but there are several real-life applications of WSN such as emergency situation, disaster management, business, offices, entertainment, school and colleges. In each application, there are several types of randomness and uncertainties. It raises multiple interferences between one node to another node and source node to destination node or amongst multiple neighbour nodes. These interferences and uncertainties are main causes of imprecise information and network troubles. Hence, there is a need of robustness technique that helps to reduce the above issues by controlling network parameters and select optimal path for communication between multiple users. The proposed technique is a combination of intelligent technique as well as mathematical modelling that uses fuzzy logic as an intelligent technique and quadratic programming as a mathematical modelling for solving the proposed goal. The combination of both provides a robustness technique that uses two basic parameters as energy and distance for selecting optimal route of the WSN.

The roadmap of the paper is as follows. Unit 2 described some information about existing works. Unit 3 illustrated the basic preliminaries information related to the proposed method. Unit 4 describes the details of the proposed method. Unit 5 describes the simulation analysis. And Unit 6 concludes the paper.

#### **2** Literature Review

In several years, various works are proposed in the context of WSN along with its variations. Some works are discussed in this section as follows. Movassagh and Aghdasi [5] designed a game theory-based scheduling algorithm for WSN. In this method, some nodes are active, and some other nodes are in sleep for optimizing the network lifetime and reducing the redundancy in coverage system. Finally, it helps in enhancing the network lifetime and network metrics of the WSN using the strategy management technique of WSN. Chen et al. [6] proposed a method for WSN based on game theory technique. This game theory technique is based on evolutionary system that is used to control and manage selfish nodes of the network. In WSN, the number of nodes is more for handling any operation. So, behaviour of the selfish nodes fluctuated frequently. The proposed method helps to

manage packet forwarding system of the node by optimizing strategy of the network and increase fitness of the WSN. Sun et al. [7] proposed a technique for spectrum sharing in WSN where the nature of the network is heterogeneous. This is based on game theory optimization technique. In this network, several types of nodes are available where each node tries to enhance its own profit which degrades the performance of the network. The game theory optimization technique helps to establish a strategy where no one deviates the rule of the game and optimizes the network metrics efficiently. Yang et al. [8] designed an intelligent system for transportation system in wireless network. This is based on an existing transportation system based on process-structured system. Finally, it helps to enhance network capabilities and services of the network. It also helps to the user function and usages in the network and network metrics properly to maintain the network. Loganathan and Subbiah [9] designed an energy-based communication system for device-to-device communication in the network. It is based on multi-criteria decision-making system where multiple criteria are involved for integrating the network metrics efficiently. Finally, it helps to enhance the network lifetime and helps in communication system. Shen et al. [10] designed a predictable-based routing method for ad hoc network. In this work, topology is organized by the helps to static and dynamic topology distribution with the help of not completely predictable method. Here, incomplete predictable technique is initiated by anti-pheromone system. Finally, it achieves energy efficiency and node utilization both for enhancing the network lifetime. Chatterjee and Das [11] designed an ACO-based routing technique for MANET. The main aim of this routing method for enhancing the QoS is by increasing ratio of packet delivery ratio and decreasing network delay by using ant. This method uses DSR routing as a base routing protocol. The basic route packets like RREQ and RREP are used here-"request ant" and "reply ant" packet for managing the network. Finally, it determined the level of pheromone for each route to decide optimal route of the network. Fatemidokht and Rafsanjani [12] designed an anomaly detection method for VANET based on clustering approach. In this paper, VANET contains some malicious nodes that act as several vehicles in the area of transportation. The nodes in this work disconnect and organize frequently in terms of changes of topology. The clustering method in this work is used for decision of gateway selection, proper neighbour selection, and also cluster head selection. Finally, it helps in packet delivery ratio and reduction of endto-end delay. Jat et al. [13] designed an intelligent technique for QoS in WLAN. This proposal is based on video delivery system. This is based on multimedia application for video data processing and analysing. The data is analysed here based on real-time data generated by the Internet. It also helps in video data transmission, storage, evaluating, and broadcasting. In WSN, data is gathered from multiple homogeneous or heterogeneous sources because real-life data is connected with different IoT, IoV, or cloud environment. So, it is difficult to keep the natures of the data in same structure. Information retrieval [14] is very important part in modern research areas which indicates collect information that is stored in unstructured form based on multiple local languages and processes it in particular pattern after observing. Hao et al. [15] designed an evaluation system for big data analysis. This data is based on IoV where it means Internet of vehicle. This proposal is based on K-means algorithm that is used

here as a clustering. In this work, different behaviours of the driving are involved for controlling vehicle. Finally, it helps in reducing fuel consumption and helps in transportation globally. Das and Tripathi [16] proposed a method for software-defined network which is based on ad hoc manner. The main key element of this work is nonlinear formulation method which is used to optimize the network by using objective function and their constraints. Finally, it helps to manage conflicting strategies of the network efficiently. Singh et al. [17] designed an optimized-based localization system for WSN. This work is based on communication between anchor and target nodes. It helps to optimize several issues such as localization, organization, security, scheduling of task, routing, lifetime of the network, and computation of data. These fusions are handled and optimized with the help of PSO and H best PSO, where H indicates Hilbert trajectory technique for the optimization. Kotary and Nanda [18] proposed a distributed-based optimization for WSN. It is based on diffusion system of the WSN which indicates K-means clustering algorithm. This diffusion technique is mixed with PSO optimization technique and in identifying optimal clustering based on intra-distance system of the sensor node. The proposed method is easily helped as a robustness technique and employed as detection of outlier of the network. Mohammed et al. [19] designed an optimization technique for WANET fuzzy logic. In this system, fuzzy logic is basically used to reduce the uncertainty of the network. This work is based on clustering system where clustering is designed with the help of constraints of the fuzzy logic. The several network parameters are used as a design of fuzzy constraints such as hop count, speed, movement of the nodes, position of the nodes, and residual energy of the nodes. Finally, with the help of the stated network parameters, fitness function is designed that helps to evaluate optimal route of the network and increase productivity and throughput [20].

#### **3** Preliminaries

In this section, basic preliminaries are described that help to understand the proposed method efficiently in terms of intelligent technique as well as mathematically. Short descriptions are as follows.

#### 3.1 Linear Programming

Linear programming is used to solve linear relationship amongst objective function and constraints based on the problem and issue. In this model, objective function and constraints both are linear in nature. It easily helps to optimize different parameters in terms of finding optimal solution.

#### 3.2 Quadratic Programming

Quadratic programming is a part of nonlinear programming which relates with objective function and constraints nonlinearly. This is based on second-order polynomial technique. In this mathematical modelling, the objective function is always nonlinear in nature but constraints are linear or nonlinear based on the situation.

#### 3.3 Fuzzy Logic

Fuzzy logic is a multi-valued logic which is based on the relation between partial truth and partial false depending on degree of truth value. Degree of truth value is evaluated based on relation of universe of discourse and degree of membership function. Fuzzy logic deals with linguistic variables for reducing uncertainty of information and estimates imprecise parameters of the system.

#### 3.4 Rule-Based System

Rule-based system is a fusion of fuzzy logic and knowledge-based system. It is basically used to solve uncertainty of the system using If–Then statement. It has two basic components such as antecedent and consequent. Antecedent handles "If" clause, and consequent handles "Then" clause. It is rapidly used in several applications such as engineering and science for reducing the uncertainly of the information.

#### 4 Proposed Method

In this section, the main proposed method is illustrated with the help of two basic network parameters such as energy and distance. The purpose of these parameters is to design an optimal strategy for evaluating optimal route that enhances the network lifetime efficiently. The nature of the energy parameter is conflicting with the parameter distance because if energy is increased, then network lifetime is also increased, and if distance is increased, then network lifetime is decrease. So, energy is equal to inverse of distance parameter. In this paper, energy is considered as 500 unit, and distance is considered as 1600 unit. The membership functions of both parameters are shown in Tables 1 and 2. Network lifetime of the WSN is evaluated with these two parameters and optimization models of the proposed method shown in Eqs. (1)–(4).

Table 1         Membership           functions of energy	Linguistic variable	Notation	Notation of range	Value
	Low	$E_{\rm L}$	$[E_{L-}, E_{L+}]$	(0–150)
	Medium	E <sub>M</sub>	$[E_{\rm M-}, E_{\rm M+}]$	(100–250)
	High	$E_{\mathrm{H}}$	$[E_{\rm H-}, E_{\rm H+}]$	(180–375)
	Very High	E <sub>VH</sub>	$[E_{\rm VH-}, E_{\rm VH+}]$	(240–500)

# Table 2Membershipfunctions of distance

Linguistic variable	Notation	Notation of range	Value
Low	$D_{\mathrm{L}}$	$[D_{L-}, D_{L+}]$	(0-400)
Medium	$D_{\mathrm{M}}$	$[D_{M-}, D_{M+}]$	(350-800)
High	$D_{ m H}$	$[D_{\rm H-}, D_{\rm H+}]$	(500–1200)
Very high	$D_{ m VH}$	$[D_{\mathrm{VH}-}, D_{\mathrm{VH}+}]$	(950–1600)

Maximize: Subject to constraints	Obj <sub>1</sub> = $(x_1)^2 + (x_2)^2$ ; : $e_1x_1 + d_1x_2 \ge 500$ ; $e_2x_1 + d_2x_2 \ge 500$ ; $x_1 \ge 0$ ; $x_2 \ge 0$ ; $e_1 \ge 0$ ; $e_1 \le 150$ ; $e_2 \ge 0$ ; $e_2 \le 150$ ; $d_1 \ge 950$ ; $d_1 \le 1600$ ; $d_2 \ge 950$ ; $d_2 \le 1600$ ;	(1)
Maximize: Subject to constraints	Obj <sub>2</sub> = $(x_1)^2 + (x_2)^2$ ; : $e_1x_1 + d_1x_2 \ge 1500$ ; $e_2x_1 + d_2x_2 \ge 1500$ ; $x_1 \ge 0$ ; $x_2 \ge 0$ ; $e_1 \ge 100$ ; $e_1 \le 250$ ; $e_2 \ge 100$ ; $e_2 \le 250$ ; $d_1 \ge 500$ ; $d_1 \le 1200$ ; $d_2 \ge 500$ ; $d_2 \le 1200$ ;	(2)
Maximize: Subject to constraints	Obj <sub>3</sub> = $(x_1)^2 + (x_2)^2$ ; : $e_1x_1 + d_1y_1 \ge 2500$ ; $e_2x_1 + d_2y_1 \ge 2500$ ; $x_1 \ge 0$ ; $x_2 \ge 0$ ; $e_1 \ge 180$ ; $e_1 \le 375$ ; $e_2 \ge 180$ ; $e_2 \le 375$ ; $d_1 \ge 350$ ; $d_1 \le 800$ ; $d_2 \ge 350$ ; $d_2 \le 800$ ;	(3)

Maximize: 
$$Obj_4 = (x_1)^2 + (x_2)^2;$$
  
Subject to constraints:  $e_1x_1 + d_1x_2 \ge 3500;$   
 $e_2x_1 + d_2x_2 \ge 3500;$   
 $x_1 \ge 0; x_2 \ge 0;$   
 $e_1 \ge 240; e_1 \le 500;$   
 $e_2 \ge 240; e_2 \le 500;$   
 $d_1 \ge 0; d_1 \le 400;$   
 $d_2 \ge 0; d_2 \le 400;$   
(4)

In above-mentioned Eqs. (1)–(4), the optimization models are illustrated for network lifetime using energy and distance parameters. In these models, decision variables  $x_1$  and  $x_2$  are used for energy and inversely distance parameters based on two constraints where energy is used "Low" to "Very High" and distance is used "Very High" to "Low" due to contradictory nature of the distance parameter. In these models, a number of sensor nodes are used such as 500, 1500, 2500, and 3500 with difference of 1000 nodes. Each model is evaluated in ten iterations based on same linguistic variation relation of energy and distance parameters. In the proposed model, energy and distance are considered as input parameters and output parameters considered as network lifetime. The different values of each iteration is shown in Tables 3, 4, 5, and 6, and fuzzy relation between input and output parameters is shown in Table 7 as rule-based system.

In Tables 3, 4, 5, and 6, network lifetimes are illustrated based on different rounds and iterations. It shows that when a number of nodes are increased then network lifetime also increases based on rounding of sensor nodes. It indicates, during data transmission, network topology is changed, sometime route is bad, sometime route is good, or sometime route is moderate that varies based on the theorem of the fuzzy logic. Table 7 shows rule-based system including antecedents and consequents that are attached with two input parameters, i.e. energy and distance and output parameter, i.e. network lifetime (NL). In this system, distance parameter is mapped reverse way

S. No.	Low energy	Very High distance	<i>x</i> <sub>1</sub>	<i>x</i> <sub>2</sub>	Obj1
1	30,150	950,1600	0.1660206E-01	0.5257915	0.2767323
2	50,140	1000,1500	0.2492657E-01	0.4987537	0.2493766
3	80,120	1050,1550	0.3607258E-01	0.4734421	0.2254486
4	90,110	1150,1450	0.3382011E-01	0.4321358	0.1878852
5	70,100	1250.1350	0.8842397E-01	0.3987496	0.1594998
6	60,130	1200,1390	0.2075928E-01	0.4156287	0.1731782
7	10,90	1110,1490	0.4062012E-01	0.45041398	0.2028891
8	40,80	1150,1300	0.1510622E-01	0.4342572	0.1888075
9	0,100	1100,1500	0.5304115E-04	0.4545455	0.2066116
10	20,110	960,1580	0.1082386E-01	0.5206078	0.2711497

Table 3 Values of ten iterations for first model based on "Low" energy and "Very High" distance

S. No.	Medium energy	High distance	<i>x</i> <sub>1</sub>	<i>x</i> <sub>2</sub>	Obj <sub>2</sub>
1	120,240	520,1100	0.632002	2.738769	7.900261
2	140,230	540,1150	0.6747605	2.602840	7.230077
3	150,200	640,1000	0.5207142	2.221708	5.207128
4	130,190	600,1050	0.5173460	2.387908	5.969753
5	100,250	510,1200	0.5553337	2.832288	8.330248
6	150,220	700,900	0.4390244	2.048781	4.390244
7	160,210	750,950	0.4080676	1.912946	3.825880
8	110,180	650,1030	0.3796273	2.243448	5.177174
9	125,170	550,930	0.5893653	2.593326	7.072692
10	115,230	540,1170	0.5658695	2.657269	7.381284

 Table 4
 Values of ten iterations for second model based on "Medium" energy and "High" distance

 Table 5
 Values of ten iterations for third model based on "High" energy and "Medium" distance

S. No.	High energy	Medium distance	$x_1$	<i>x</i> <sub>2</sub>	Obj <sub>3</sub>
1	190,370	370,750	2.745668	5.346819	36.12717
2	200,350	390,700	2.602854	5.075459	32.56514
3	210,320	410,710	2.474132	4.830322	29.45335
4	220,300	400,740	2.639204	4.798438	29.99040
5	180,375	350,800	2.905053	5.648830	40.34861
6	230,295	380,720	2.914363	4.814991	31.67765
7	240,300	390,620	2.861168	4.649537	29.80448
8	260,350	380,680	3.066017	4.481146	29.48113
9	215,290	360,780	3.057014	5.118728	35.54671
10	195,360	395,720	2.5122871	5.088871	32.20819

 Table 6
 Values of ten iterations for fourth model based on "Very High" energy and "Low" distance

S. No.	Very High energy	Low distance	<i>x</i> <sub>1</sub>	<i>x</i> <sub>2</sub>	Obj <sub>4</sub>
1	280,350	120,300	10.56028	4.526017	132.0043
2	250,450	100,350	12.06896	4.827602	168.9655
3	260,480	110,380	11.41781	4.830625	153.7014
4	290,490	50,200	11.72056	2.020736	141.4550
5	300,500	30,250	11.55113	1.155396	134.7635
6	240,300	150,350	10.48691	6.554280	152.9338
7	260,360	90,260	12.02112	4.161206	161.8230
8	280,460	130,370	10.28331	4.774409	128.5414
9	290,430	20,210	12.01184	0.8283709	144.9704
10	315,410	40,320	10.93481	1.388375	121.4976

Table / Rule-ba	Table 7 Rule-based system of the proposed method				
Rule No.	Description				
Rule 1	If Energy is $E_L$ and Distance is $D_{VH}$ then Network Lifetime is $NL_1$				
Rule 2	If Energy is $E_L$ and Distance is $D_H$ then Network Lifetime is $NL_2$				
Rule 3	If Energy is $E_L$ and Distance is $D_M$ then Network Lifetime is $NL_3$				
Rule 4	If Energy is $E_L$ and Distance is $D_L$ then Network Lifetime is $NL_4$				
Rule 5	If Energy is $E_{\rm M}$ and Distance is $D_{\rm VH}$ then Network Lifetime is NL <sub>5</sub>				
Rule 6	If Energy is $E_{\rm M}$ and Distance is $D_{\rm H}$ then Network Lifetime is NL <sub>6</sub>				
Rule 7	If Energy is $E_{\rm M}$ and Distance is $D_{\rm M}$ then Network Lifetime is NL <sub>7</sub>				
Rule 8	If Energy is $E_{\rm M}$ and Distance is $D_{\rm L}$ then Network Lifetime is NL <sub>8</sub>				
Rule 9	If Energy is $E_{\rm H}$ and Distance is $D_{\rm VH}$ then Network Lifetime is NL <sub>9</sub>				
Rule 10	If Energy is $E_{\rm H}$ and Distance is $D_{\rm H}$ then Network Lifetime is NL <sub>10</sub>				
Rule 11	If Energy is $E_{\rm H}$ and Distance is $D_{\rm M}$ then Network Lifetime is NL <sub>11</sub>				
Rule 12	If Energy is $E_{\rm H}$ and Distance is $D_{\rm L}$ then Network Lifetime is NL <sub>12</sub>				
Rule 13	If Energy is $E_{\rm VH}$ and Distance is $D_{\rm VH}$ then Network Lifetime is NL <sub>13</sub>				
Rule 14	If Energy is $E_{\rm VH}$ and Distance is $D_{\rm H}$ then Network Lifetime is NL <sub>14</sub>				
Rule 15	If Energy is $E_{\rm VH}$ and Distance is $D_{\rm M}$ then Network Lifetime is NL <sub>15</sub>				
Rule 16	If Energy is $E_{\rm VH}$ and Distance is $D_{\rm L}$ then Network Lifetime is NL <sub>16</sub>				

 Table 7
 Rule-based system of the proposed method

with energy parameter. Hence, linguistic behaviour of the NL is shown in Table 8 and feasible, and optimal values of each rounds are shown in Tables 9, 10, 11, and 12.

In Table 8, several linguistic variables are shown based on chronological order of their increment behaviour of degree of membership or degree of truth value. It shows rule number 16 is the highest priority, i.e.  $NL_{16}$  having "Very High" energy and "Low" distance associates linguistic variable is "Too Excellent". In Tables 9, 10, 11, and 12, feasible and optimal values are shown based on round 1–4 based on

Linguistic variable Marginally
Marginally
Good
Good
Perfect
Very good
Highly good
Outstanding
Excellent
Too excellent

**Table 8**Linguistic variableof the output parameternetwork lifetime

Obj <sub>1</sub>	Residual energy $(x_1)$	Distance $(x_2)$	Low residual energy	Very high distance
0.2767323	0.1660206E-01	0.5257915	$e_1 = 30$	$d_1 = 950$
			$e_2 = 150$	$d_2 = 1600$
0.2711497	0.1082386E-01	0.5206078	$e_1 = 20$	$d_1 = 960$
			$e_2 = 110$	$d_2 = 1580$

 Table 9
 Dataset for round 1 under 500 sensor nodes for rule 1

 Table 10
 Dataset for round 2 under 1500 sensor nodes for rule 6

Obj2	Residual energy( $x_1$ )	Distance $(x_2)$	Medium residual energy	High distance
8.330248	0.5553337	2.832288	$e_1 = 100$	$d_1 = 510$
			$e_2 = 250$	$d_2 = 1200$
7.900281	0.632002	2.738769	$e_1 = 120$	$d_1 = 520$
			$e_2 = 240$	$d_2 = 1100$

 Table 11
 Dataset for round 3 under 2500 sensor nodes for rule 11

Obj3	Residual energy $(x_1)$	Distance $(x_2)$	High residual energy	Medium distance
40.34861	2.905053	5.648830	$e_1 = 180$	$d_1 = 350$
			$e_2 = 375$	$d_2 = 800$
36.12717	2.745668	5.346819	$e_1 = 190$	$d_1 = 370$
			$e_2 = 370$	$d_2 = 750$

 Table 12
 Dataset for round 4 under 3500 sensor nodes for rule 16

Obj4	Residual energy $(x_1)$	Distance $(x_2)$	Very high energy	Low distance
168.9655	12.06896	4.827602	$e_1 = 250$	$d_1 = 100$
			$e_2 = 450$	$d_2 = 350$
161.8230	12.02112	4.161206	$e_1 = 260$	$d_1 = 90$
			$e_2 = 360$	$d_2 = 260$

sensor nodes 500, 1500, 2500, and 3500 using rule numbers 1, 6, 11, and 16. Here, highest value indicates optimal decision, and lowest value indicates feasible value. Hence, optimal route is based on energy having "Very High" and distance having "Low".

#### 5 Simulation and Analysis

In this section, details of simulation and analysis are illustrated. The proposed method is simulated in LINGO optimization software based on fusion of linear and nonlinear formulations. The proposed method is simulated and verified in four optimization models based on four rounds where each round is repeated ten times based on different data set of same linguistic variable. The parameters details are shown in Table 13.

Figures 2, 3, 4, and 5 show feasible solutions of the optimization model based on sensor nodes 500 in round 1, 1500 in round 2, 2500 in round 3, and 3500 in round 4. In each round, data is tested 10 times based on same rule-based system. Data is shown in Tables 3, 4, 5, and 6, and their feasible and optimal data set is shown in Tables 9, 10, 11, and 12 based on rule-based system mentioned in Table 7 with linguistic behaviour mentioned in Table 8. First feasible value of network lifetime is 0.2711497 based on "Low" energy and "Very High" distance. Second feasible value of network lifetime is 7.900281 based on "Medium" energy and "High" distance. Third feasible value of network lifetime is 36.12717 based on "High" energy and "Medium" distance. Fourth feasible value of network lifetime is 161.8230 based on "Very High" energy and "Low" distance. Based on all feasible values, it is observed that when a number of nodes are increased as 500, 1500, 2500, and 3500, then network lifetime is also increased.

Parameter	Description
Windows	Windows 10 pro
MS Office	2013
Optimization software	LINGO
Energy	500 unit
Distance	1600 unit
Optimization	Maximization
Input parameters	Two (energy, distance)
Output parameter	Network lifetime
Total rules	16
Rounds	4
Iterations	$4 \times 10$
Objective functions	4
Constraints	$4 \times 2$
Nature of objectives	Nonlinear
Nature of constraints	Linear
Number of nodes	500-3500
Linguistic variables of energy	4
Linguistic variables of distance	4

## Table 13Simulationparameter details

Solution Report - Sun P4 O1.10				
Global optimal solution four	nd.	495/2020/02/2020		1
Objective value:		0.2711497		
Infeasibilities:		0.5231056E-05		
Total solver iterations:		9		
Elapsed runtime seconds:		0.05		
Model is convex quadratic				
Model Class:		QP		
Total variables:	6			
Nonlinear variables:	2			
Integer variables:	0			
Total constraints:	13			
Nonlinear constraints:	1			
Total nonzeros:	16			
Nonlinear nonzeros:	2			
	Variable	Value	Reduced Cost	
	X1	0.1082386E-01	-0.4425554E-04	
	X2	0.5206078	0.9319766E-06	
	El	150.0000	0.000000	
	E2	150.0000	0.000000	
	D1	1600.000	0.000000	
	D1 D2			
	D2	1600.000	0.000000	
	Row	Slack or Surplus	Dual Price	
	1	0.2711497	-1.000000	
	2	-0.5231056E-05	-0.1084599E-02	
	3	323.7510	0.000000	
	4	0.1082386E-01	0.000000	
	5	0.5206078	0.000000	
	6	150.0000	0.000000	
	7	0.000000	0.000000	
	8	150.0000	0.000000	
	9	0.000000	0.000000	
	10	650.0000	0.000000	
	11	0.000000	0.000000	
	12	650.0000	0.000000	
	13	0.000000	0.000000	

Fig. 2 Feasible solution for network lifetime in round 1 under 500 nodes

Figures 6, 7, 8, and 9 show optimal solutions of the optimization model based on sensor nodes 500 in round 1, 1500 in round 2, 2500 in round 3, and 3500 in round 4. In each round, data is tested 10 times based same rule-based system. Data is shown in Tables 3, 4, 5, and 6, and their feasible and optimal data set is shown in Tables 9, 10, 11, and 12 based on rule-based system mentioned in Table 7 with linguistic behaviour mentioned in Table 8. First optimal value of network lifetime is 0.2767323 based on "Low" energy and "Very High" distance. Second optimal value of network lifetime is 8.330248 based on "Medium" energy and "High" distance. Third optimal value of network lifetime is 40.34861 based on "High" energy and "Very High" energy and "Medium" distance. Fourth optimal value of network lifetime is 168.9655 based on "Very High" energy and "Low" distance. Based on all feasible values, it is observed that when a number of nodes are increased as 500, 1500, 2500, and 3500, then network lifetime is also increased.

olution Report - Sun P4 O2.1				
Global optimal solution four	nd.			
Objective value:		7.900281		
Infeasibilities:		0.1601972E-05		
Total solver iterations:		8		
Elapsed runtime seconds:		0.05		
Model is convex quadratic				
Model Class:		QP		
Total variables:	6			
Nonlinear variables:	2			
Integer variables:	0			
Total constraints:	13			
Nonlinear constraints:	1			
Total nonzeros:	16			
Nonlinear nonzeros:	2			
	Variable	Value	Reduced Cost	
	Xl	0.6320002	-0.4456942E-04	
	X2	2.738769	0.1028325E-04	
	E1	250.0000	0.000000	
	E2	250.0000	0.000000	
	D1	1200.000	0.000000	
	D2	1200.000	0.000000	
	Row	Slack or Surplus	Dual Price	
	1	7.900281	-1.000000	
	2	-0.1601972E-05	-0.1053371E-01	
	3	1664.326	0.000000	
	4	0.6320002	0.000000	
	5	2.738769	0.000000	
	6	150.0000	0.000000	
	7	0.000000	0.000000	
	8	150.0000	0.000000	
	9	0.000000	0.000000	
	10	700.0000	0.000000	
	11	0.000000	0.000000	
	12	700.0000	0.000000	
	13	0.000000	0.000000	

Fig. 3 Feasible solution for network lifetime in round 2 under 1500 nodes

Global optimal solution fou	nd.			
Objective value:		36,12717		
Infeasibilities:		0.3281541E-06		
Total solver iterations:		8		
Elapsed runtime seconds:		0.03		
Model is convex quadratic				
Hodel Class:		QP		
Total variables:	6			
Nonlinear variables:	2			
Integer variables:	0			
Total constraints:	13			
Nonlinear constraints:	1			
Total nonzeros:	16			
Nonlinear nonzeros:	2			
	Variable	Value	Reduced Cost	
	X1	2.745668	0.6186056E-05	
	X2	5.346819	-0.3177358E-05	
	El	375.0000	0.000000	
	E2	375.0000	0.00000	
	D1	800.0000	0.000000	
	D2	800.0000	0.000000	
	Row	Slack or Surplus		
	1	36.12717	-1,000000	
	2	-0.3281541E-06		
	3	2526.012	0.000000	
	4	2.745668	0.000000	
	5	5.346819	0.00000	
	6	195.0000	0.000000	
	7	0.000000	0.000000	
	8	195.0000	0.00000	
	9	0.000000	0.000000	
	10	450.0000	0.000000	
	11	0.000000	0.000000	
	12	450.0000	0.000000	

Fig. 4 Feasible solution for network lifetime in round 3 under 2500 nodes

Solution Report - Sun P4 04.7	15			
Global optimal solution fou	nd.			
Objective value:		161.8230		
Infeasibilities:		0.3713634E-05		
Total solver iterations:		8		
Elapsed runtime seconds:		0.05		
Model is convex quadratic				
Model Class:		QP		
Total variables:	6			
Nonlinear variables:	2			
Integer variables:	0			
Total constraints:	13			
Nonlinear constraints:	1			
Total nonzeros:	16			
Nonlinear nonzeros:	2			
	Variable	Value	Reduced Cost	
	X1	12.02112	-0.2997508E-04	
	X2	4.161206	0.8655425E-04	
	El	500.0000	0.000000	
	E2	500.0000	0.000000	
	D1	400.0000	0.000000	
	D2	400.0000	0.000000	
	Row	Slack or Surplus	Dual Price	
	1	161.8230	-1.000000	
	2	-0.3713634E-05	-0.9247028E-01	
	3	1909.517	0.000000	
	4	12.02112	0.000000	
	5	4.161206	0.000000	
	6	260.0000	0.000000	
	7	0.000000	0.000000	
	8	260.0000	0.000000	
	9	0.000000	0.000000	
	10	400.0000	0.000000	
	11	0.000000	0.000000	
	12	400.0000	0.000000	
	13	0.000000	0.000000	

Fig. 5 Feasible solution for network lifetime in round 4 under 3500 nodes

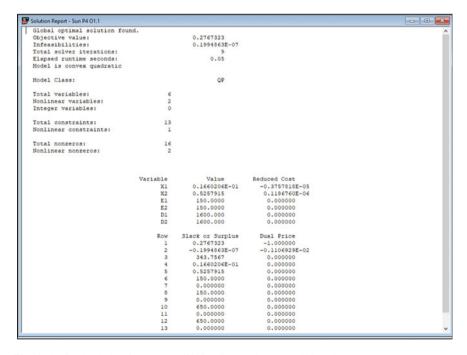


Fig. 6 Optimal solution for network lifetime in round 1 under 500 nodes

Solution Report - Sun P4 O2.5				
Global optimal solution fou	nd.			
Objective value:		8.330248		
Infeasibilities:		0.1245186E-05		
Total solver iterations:		8		
Elapsed runtime seconds:		0.05		
Model is convex quadratic				
Model Class:		QP		
Total variables:	6			
Nonlinear variables:	2			
Integer variables:	0			
Total constraints:	13			
Nonlinear constraints:	1			
Total nonzeros:	16			
Nonlinear nonzeros:	2			
	X1 X2 E1 E2 D1 D2	0.5553337 2.832288 250.0000 250.0000 1200.000 1200.000	-0.3234236E-04 0.6338096E-05 0.000000 0.000000 0.000000 0.000000 0.000000	
	Row	Slack or Surplus	Dual Price	
	1	8.330248	-1.000000	
	2	-0.1245186E-05	-0.1110700E-01	
	3	2037.578	0.000000	
	4	0.5553337	0.000000	
	5	2.832288	0.000000	
	6	150.0000	0.000000	
	7	0.000000	0.000000	
	8	150.0000	0.000000	
	9	0.000000	0.000000	
	10	700.0000	0.000000	
	11	0.000000	0.000000	
	12	700.0000	0.000000	
	13	0.000000	0.000000	

Fig. 7 Optimal solution for network lifetime in round 2 under 1500 nodes

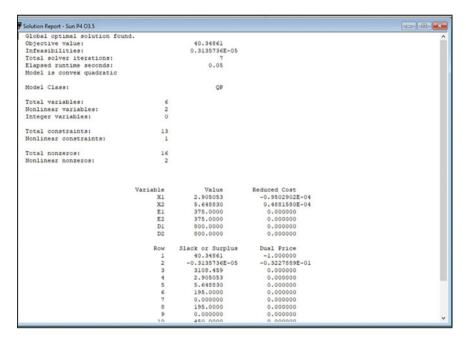


Fig. 8 Optimal solution for network lifetime in round 3 under 2500 nodes

olution Report - Sun P4 04.2				
Hobal optimal solution fou	nd.			
Objective value:		168.9655		
Infeasibilities:		0.4812933E-06		
Total solver iterations:		8		
Elapsed runtime seconds:		0.05		
fodel is convex quadratic				
Hodel Class:		QP		
Total variables:	6			
ionlinear variables:	2			
integer variables:	0			
Total constraints:	13			
Nonlinear constraints:	1			
Total nonzeros:	16			
Sonlinear nonzeros:	2			
	Variable	Value	Reduced Cost	
	X1	12.06896	-0.1246659E-04	
	X2	4.827602	0.3115854E-04	
	El	500.0000	0.000000	
	E2	500.0000	0.000000	
	D1	400.0000	0.000000	
	D2	400.0000	0.000000	
	Row	Slack or Surplus	Dual Price	
	1	168.9655	-1.000000	
	2	-0.4812933E-06	-0.9655172E-01	
	3	3620.692	0.000000	
	4	12.06896	0.000000	
	5	4.827602	0.000000	
	6	260.0000	0.000000	
	7	0.000000	0.000000	
	8	260.0000	0.000000	
	9	0.000000	0.000000	
	10	400.0000	0.000000	
	11	0.000000	0.000000	
	12	400.0000	0.000000	
	13	0.000000	0.000000	

Fig. 9 Optimal solution for network lifetime in round 4 under 3500 nodes

#### 6 Conclusions

In this paper, network lifetime is optimized with the help of two basic parameters such as energy and distance. Nature of energy parameter is same as nature of network lifetime, but nature of distance parameter is different from the nature of network lifetime. So, the combination of energy and inverse of distance is used to form rule-based system for analysing route of the network. Fuzzy logic helps to estimate uncertainty of the network using membership function and mapped the imprecise network parameters efficiently. Decision-maker of the proposed model analyses the route of the network from source to destination nodes based on two efficiency terms as feasible and optimal. Feasible route indicates nearby best route which is the second choice of the route selection. Optimal route is the best choice for route selection from source node to the destination node. The optimal route is efficiently used to transmit the data packet within the WSN. This route helps to reduce energy consumption of the nodes and solve the ambiguity of the route selection in the network within several variations of the parameters.

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