K NEAREST NEIGHBOR LOGISTIC REGRESSION FOR STABLE AND CONSISTENT DATA DELIVERY IN WSN

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***Abstract*— Wireless Sensor Network (WSN) is a collection of sensor nodes with self-arranged and organizational structure-less wireless networks. WSN performs better network communication to attain stable and consistent performance. Additionally, consistent wireless network communication is provided between the sensor nodes. But, it attains maximum data loss and delay during data transmission. In order to overcome above issues, K Nearest Neighbour-based Logistic Regression (KNN-LR) framework is developed. Stability-aware Logistic Regression model and Link Quality-based Consistent are two different phases for wireless network communication. In the beginning, Stability-aware Logistic Regression model is designed in WSN. Here, local and global pivotal values are measured with neighbors' to make the decision regarding existence or non-existence of a sensor node. Additionally, machine learning logistic regression algorithm is utilized to achieve stable network with enhanced network lifetime and throughput. After that, consistent wireless network communication is attained by using the basis of link quality in WSN. The link quality enhances the consistency of network by selecting optimal route path during data transmission. As a result, data loss and end to end delay is minimized with efficient route path. The simulation is carried out to analyze the performance of proposed KNN-LR framework with the parameters such as throughput, network lifetime, data loss and end to end delay.**

***Index Terms*— Wireless sensor networks, Logistic Regression model, Fusion Center, data Packet Acceptance Ratio**

I. INTRODUCTION

Wireless sensor networks attain stable and high consistent data delivery with the required performance of data communication. Here, stable network topology is developed for effective wireless communication. Quality of services plays a vital role for improving the data transmission in WSNs. Therefore, the several research works has been established in WSN and it explained with the help of literature.

Competence-enhanced and Maintenance Distance Vector (MC-DV) framework [1] differentiate the links in the network. With the distribution of every link to an end-to-end (E2E) path, transmission power and retransmission were adjusted. Thus, it improves packet delivery ratio and reduces energy utilization. But, the network lifetime was minimized by using Competence. Security Fault Tolerant Routing (SFTR) was presented in [2] to develop the security of network operation and data transmission. However, it attains higher delay during data transmission.

Moment stability was presented in [3] with a network stability criterion to provide light-weighted traffic on network. Based on primary and secondary user activities, network stability was obtained from these circumstances. In [4], Stable-Aware Evolutionary Routing Protocol (SAERP) was developed to obtain maximum stability and minimum instability in WSNs. Thus, end-to-end delay of data transmission was increased due to minimum packet delivery ratio.

A stable and energy-efficient routing technique in [5] was introduced to provide continuous communication. According to routing protocol, energy consumption is minimized by calculating a route selection probability. Similarly, in [6] stable energy efficient clustering protocol was provided to attain stable routing. Thus, data communication is more effective due to better energy utilization and network lifetime in WSNs. However, throughput is reduced with minimum energy efficiency.

Head-of-line access delay-based scheduling algorithm was introduced in [7] which program the flow of Transmission Control Protocol. As a result, network throughput is enhanced. However, the link stability was not considered. Integrity and Delay Differentiated Routing (IDDR) was presented in [8] to achieve stable routing by utilizing Lyapunov drift techniques. But, it failed to improve the data delivery rate.

In [9], Mobile Data Collection based approach was considered with collection and communication strategy. This two-pronged strategy minimizes the latency during data transmission. But, energy consumption is higher. The centralized and heuristic algorithms namely Tabu and Domino were developed in [10] to perform minimum delay. However, higher data packets are dropped during transmission. The issues presented in the existing literature such as data loss and delay. In order to overcome such issues, K Nearest Neighbour-based Linear Regression (KNN-LR) framework is developed in WSN. The main contribution of the research work is described as follows,

- K Nearest Neighbour-based Logistic Regression (KNN-LR) framework performs effective data packet delivery. Stability-aware logistic regression model measures local and global pivotal values. Based on the measured values, target node is selected for data packet transmission. By using Maximum conditional likelihood in the network, a decision regarding the existence or non-existence of sensor node is achieved.
- Machine learning logistic regression algorithm is designed in WSN to obtain improved throughput and network lifetime. Then, link quality is used to select optimal route path to transmit packet with neighbouring nodes. According to sensor node distance, data packet acceptance ratio is measured. This ensures consistency during wireless network communication. As a result, it attains minimum data loss and delay during transmission.

The rest of the paper is structured as follows: In Section 2, K Nearest Neighbour-based Linear Regression (KNN-LR) framework is described with neat diagram. In Section 3, simulation settings are provided with the analysis of results explained in Section 4. In Section 5, introduces the related works. The conclusion of the research work is presented in section 6.

II. K NEAREST NEIGHBOUR BASED LOGISTIC REGRESSION FRAMEWORK

A K Nearest Neighbour based Logistic Regression (KNN-LR) framework is proposed to proficiently handle the sensor nodes in the network and develops the entire network performance. The proposed KNN-LR framework uses a local or global pivotal value for exchanging the packets between the neighbors. With the support of their neighbors' sensors through the fusion center (FC), a conclusion about the senor nodes existence or non-existence is provided.

Let us consider, proposed KNN-LR framework consists of 'n' energy harvesting sensors nodes that are arbitrarily distributed in a two-dimensional area 'a * a'. Each sensor node in network is prepared with omni-directional receiver and has a definite radio transmission range 'd'. Thus, energy model and wireless link model is used to obtain wireless network communication. The block diagram of KNN-based Logistic Regression (KNN-LR) framework is shown in below figure 1

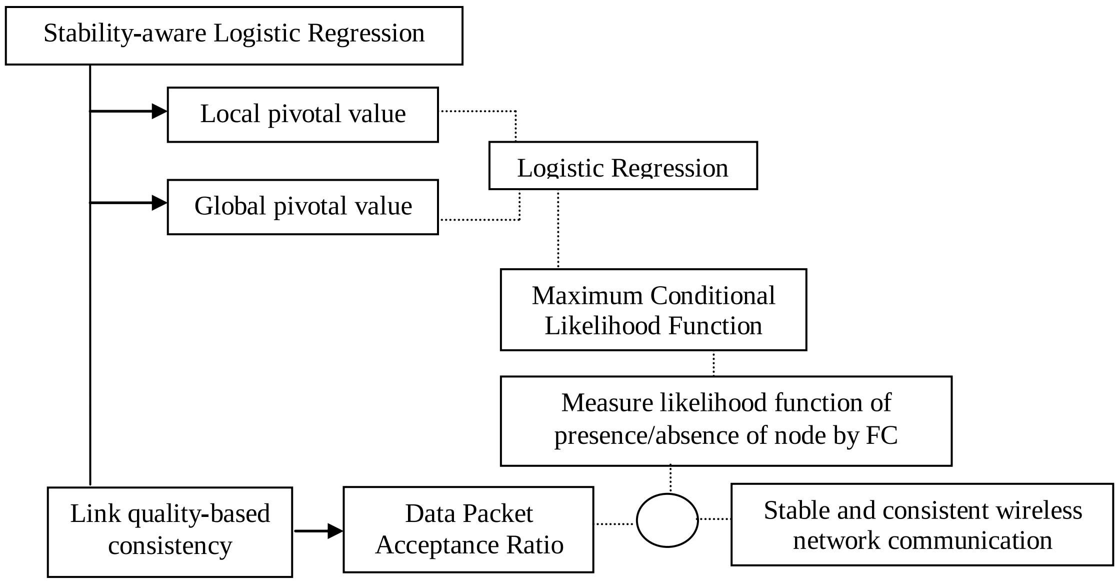

Figure 1 Block diagram of KNN-based Logistic Regression

From the figure 1, KNN-LR framework consists of two folds such as Stability-aware Logistic Regression (SLR) model and Link quality-based consistency. Initially, SLR model is provided to achieve a stable network communication and the local/global pivotal value is arrived. With the help of obtained values, Maximum Conditional Likelihood Function (MCLF) is used by FC to exchange the packets between neighbors. Thus, stability is said to be achieved for wireless network communication between neighbors. Next, link quality between the nodes is designed and optimal route is selected for data packet transmission. Based on the distance measured between the nodes, consistency is said to be arrived at in WSN.

2.1 Stability-aware Logistic Regression

The network model is assumed to develop a joint optimized stable and consistent wireless network communication framework.In order to achieve a stable network communication, proposed framework included a two-dimensional space in which sensor nodes are randomly distributed in a network. Additionally, related computing and communication range is considered by all the sensor nodes in network with omnidirectional manner. Thus, it secures communication between sensor nodes.

In addition to that, network model of wireless network consists of a graph '$G(V, E)$'. Here, 'V' indicates the set of sensor nodes and 'E' represents the set of edges denoting the links between the neighboring nodes. For example, an edge is considered from sensor node 'a' to 'b' and it is given as '(a, b)'. A path 'P' is developed from 'v_1' to 'v_n' be denoted as '$P(v_1, v_n)$'.

2.2 Integration Rule-based Local Pivotal factor

At first, the local pivotal value is obtained according to the data packets that are exchanged between neighbors. With the help of integration rule'k/n', local pivotal value is arrived and final state decision is determined by using fusion center (FC). From the integration rule, the 'k' Nearest Neighbour sensor nodes are analyzed fortransferring 'k' nearest neighborswith a weight '$1/k$' and others sensor nodes are assigned with '0' weight.When a single sensor node transmitsthe data to fusion center, then the Integration Rule by the KNN-LR framework is given below.

$$R_1 = \sum_{i=1}^{n} T_j \geq k \qquad (1)$$

From (1), 'R_1' denotes integration rule by single sensor nodes and 'T_j' is target node. When '$j = 1$', target node is presented whereas '$j = 0$' denotes absence of target node according to total sensor node 'n'. When k nearest neighbour value is more than '1', FC choose the data from local sensors and makes a positive decision. Similarly, Integration Rule is produced when several sensor nodes transmit data to the fusion center and it is formulated as below

$$R_2 = \frac{\sum_{i=1}^{n} T_j}{SN \to D} \geq k \qquad (2)$$

The integration rule for several sensor node 'R_2' is given in (2) and number of sensor node transmit the data to FC is specified as '$SN \to D$'. Here, the target node is given as 'T_j' and their presence or absence is denoted by either '$j = 1$' or '$j = 0$' respectively. After measuring the local pivotal value, the global pivotal value is arrived based on a threshold value.

2.3 Tally Rule-based Global Pivotal factor

After that global pivotal value is measured with the use of tally rule. Here, the detections made by local sensor nodes are considered and then comparing it with a threshold 'α'. The tallying rule (i.e. the likelihood ratio) is given as follows.

$$R_3 = \sum_{i=1}^{n} T_j \geq \alpha (3)$$

From (3), 'n' symbolizes number of sensor nodes and 'α' signifying the threshold factor with target nodes 'T_i' in network. The local sensor false alarm rate, global sensor false alarm rate and total sensors are used to attain threshold factor. Therefore, the threshold factor is measured by using following expression.

$$\alpha = R_1 \left[\frac{T_m}{time_i}\right] + R_3 \left[\frac{T_m}{time_i}\right] + SN \to D \qquad (4)$$

From (4), 'α' is defined as the sum of local sensor false alarm rate '$R_1 \left[\frac{T_m}{time_i}\right]$', global sensor false alarm rate '$R_3 \left[\frac{T_m}{time_i}\right]$' and total sensors nodes which send data to FC '$SN \to D$' respectively.Here, sensor node is generated with intermediate sensor node which is greater than or equal to the K nearest neighbour nodes. The sensor node whose likelihood ratio 'R_3' is greater than the threshold factor 'α' is shown below figure.

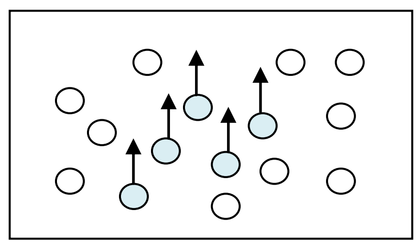

Figure 2 Data packets sent to fusion center

The data packet transmission to fusion center is described in figure 2. The upward arrows indicates the sensor nodes whose likelihood ratio is greater than the threshold factor. Only those nodes are able to send their data packets to the fusion center.For example, selection of neighbour node based on threshold factor is shown in below figure 3. From the figure, radius 'r' around the sensor nodes signify the range of transmission. The distance between source node 'S', and fusion center, 'FC' is '$D_{S \to FC}$'. When '$D_{S \to FC}$' is greater than 'α', than the likelihood ratio higher than threshold factor to forward the data packet from 'S' to 'FC'.

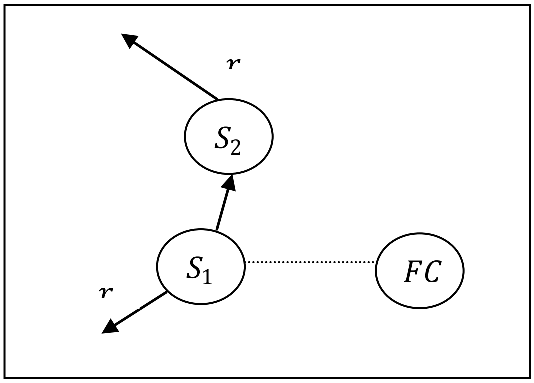

Figure 3 An example scenario of selection of a neighbour node

Figure 3 achieves higher threshold factor. Then, Logistic Regression is used with threshold factor to prepare an efficient decision about the presence or absence of target node with the help of their neighbour sensor nodes. This is expressed as given below.

$$Prob(Y=0|X=<x_1,x_2,\dots,x_n>) = \frac{1}{1+\exp\left(w_0+\sum_i w_i X_i\right)} \quad (5)$$

$$Prob(Y=1|X=<x_1,x_2,\dots,x_n>) = \frac{\exp\left(w_0+\sum_i w_i X_i\right)}{1+\exp\left(w_0+\sum_i w_i X_i\right)} \quad (6)$$

From (5) and (6), '$Prob(Y=0)$' and '$Prob(Y=1)$' denotes the absence or presence of the target node to accept the data packets in network. Here, 'w' denotes the weight and 'X_i' represents the total sensor nodes that send data packets to the FC. Then, Maximum Conditional Log Likelihood (MCLL) function is used to measure information and MCLL function send the logistic regression values to FC. The MCLL function is obtained by using following expression.

$$Prob(W) = \ln \prod_{Log} Prob(Y^{Log} \mid X^{Log}, W) = \sum_{Log} \ln Prob(Y^{Log} \mid X^{Log}, W) \quad (7)$$

$$Prob(Y=0|X,W) = \frac{1}{1+\exp\left(w_0+\sum_i w_i X_i\right)} \quad (8)$$

$$Prob(Y=1|X,W) = \frac{\exp\left(w_0+\sum_i w_i X_i\right)}{1+\exp\left(w_0+\sum_i w_i X_i\right)} \quad (9)$$

From (8) and (9), '$Y=0\,|Y=1$' denotes the presence or absence of target nodes, 'X' denotes the input sensor nodes ready for data packet transmission with weight 'W'. The data likelihood function is representedas '$\ln \prod_{Log} Prob(Y^{Log} \mid X^{Log}, W)$'. Based on node decision, the conditional likelihood function '$Log(W)$' is as given below.

$$Log(W) = \sum_{Log} Y^{Log} \ln Prob(Y^{Log}=1, X^{Log}, W) + \ln ProbYLog=0, XLog, W \quad (10)$$

$$= \sum_{Log} Y^{Log} \ln \frac{Prob(Y^{Log}=1 \mid X^{Log}, W)}{Prob(Y^{Log}=0 \mid X^{Log}, W)} + \ln Prob(Y^{Log} = 0 \,/\, XLog, W \quad (11)$$

From (10) and (11), likelihood function is measured, Here, 'Y' represent the training samples or sensor nodes for data packet transmission. Below algorithm describes the pseudo code representation for optimized decision with fewer packets.

Input: fusion center (FC), Target Node 'T_j', Sensor Node 'SN',
Output: Improved throughput and network life time with stable network communication
Step1. **Begin**
Step 2. **Repeat**
Step3. **For** each Sensor Node 'SN' with detected Target Node 'T_j'
Step 4. **For** 'k' neighbouring nodes
Step5. Measure Local Pivotal Factor using (2)
Step6. Measure Global Pivotal Factor using (3)
Step7. Obtain threshold factor 'α' using (4)
Step8. Obtain the weights for each sensor node using (5) and (6)
Step9. Measure Maximum Conditional Log Likelihood function using (7)
Step10. Measure Conditional Log Likelihood function using (10)
Step11. **End for**
Step12. **End for**
Step13. **Until** (decision about the local or global presence/absence of target node is made by FC)
Step14. **End**

Algorithm 1 Pseudo code representation of Machine Learning Logistic Regression

The pseudo code representation of Machine Learning Logistic Regression (MLLR) from algorithm 1 provides three steps. At first, it obtains the presence of target node. Then fusion centre is used to obtain the data packet that has to be sent by a sensor node. With the help of local pivotal factor and global pivotal factor, data's are selected. At last, maximum conditional log likelihood function is applied to transmit data packets between neighbors.

2.4 Link Quality-based Consistent Wireless Network Communication

Finally, consistent wireless network communication in WSN is provided by means of link quality. When there is a higher link quality in network, then there is a minimum data loss and delay. With the aid of distance between two sensor nodes, consistent wireless network communication is arrived. Therefore, the block diagram of consistent measure through link quality is shown in figure 4. Hence, consistence factor is measured through link quality of sensor node based on the Data Packet Acceptance Ratio (DPAR).

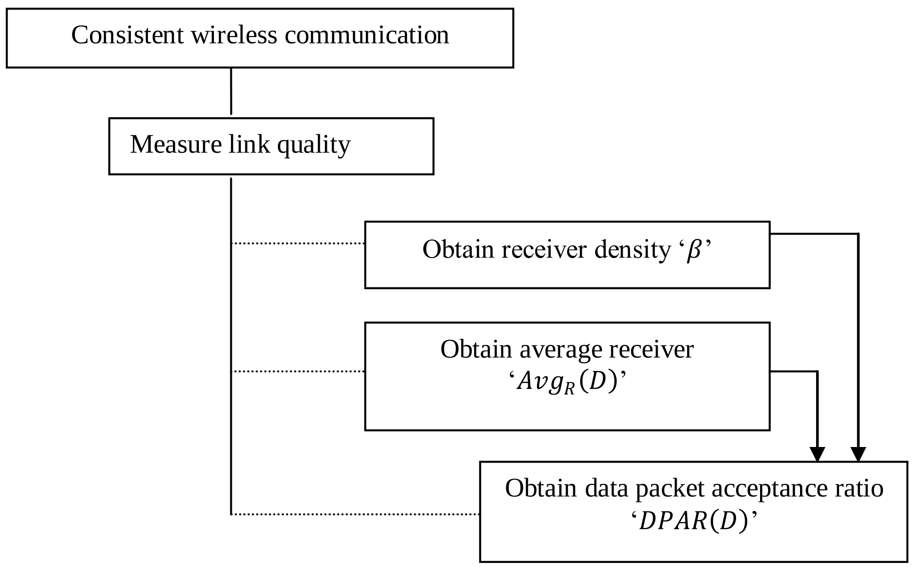

Figure 4 Block diagram of consistent measure through link quality

From figure, consistent communication is obtained. Then, the probability for receiving a data packet successfully from sender at distance 'D' is calculated by using below expression.

$$SN \rightarrow D_R = \beta Prob_{Succ}(D) \quad (12)$$

From (12), '$Prob_{Succ}(D)$' denoted the probability of successful reception and 'β' denotes the density of receiver. Then, 'β'is measured as given below.

$$\beta = \frac{(n-1)}{a^2} \quad (13)$$

From (13), 'β' is defined as ratio of number of sensor nodes '$(n-1)$' to the overall network size 'a^2' considered for network communication. The average number of receivers 'Avg_R' within distance 'D' is as given below.

$$Avg_R(D) = \beta D^2 \quad (14)$$

With the use of average receiver value, Data Packet Acceptance Ratio is measured. It is defined as the ratio of successfully received the data packets within the distance '$SN \rightarrow D_R$' to the average number of receivers 'Avg_R' within distance 'D'.

$$DPAR(D) = \frac{SN \to D_R}{Avg_R(D)} \quad (15)$$

Additionally, KNN-LR framework collects link quality to measure all obtainable routes from source node to fusion center. Then, most actual route is selected for data packet delivery. Thus,the pseudo code representation of the Distance Routing Data Packet gathering is given in algorithm 2.

Input: Sensor Nodes 'SN', Distance 'D', network size 'a^2'
Output:Consistent network communication with minimum data loss and delay
Step1: **Begin**
Step2: **For** all Sensor Nodes 'SN' within a Distance 'D'
Step3: Measure probability of successful reception using (12)
Step4: Obtain Data Packet Acceptance Ratio using (15)
Step5: **End for**
Step6: **End**

Algorithm 2 Distance Routing Data Packet gathering

The Distance Routing Data Packet gathering algorithm 2 achieves data packet transmission within the distance range 'D'. Hence, consistent network communication is established for achieving an efficient routing path for link quality measurement.Thus, routing paths are developed during the data packet forwarding phase. It ensuring consistency in the network and reduces the data loss with minimum delay.

III. SIMULATION SETTINGS

The proposed KNN-based Logistic Regression (KNN-LR) framework is simulated using NS-2 simulator with the network range of 1200*1200 m size.To conduct the experimental work, Destination Sequence Based Distance Vector (DSDV) is used as routing protocol with different 100 nodes and 90 data packets with varies sizes. The moving speed is about 10 m/s for each sensor node with a simulation rate of 45 millisecondsfor data transmission. Here, the mobility of source node and intermediate nodes was denoted by several random locations.

IV. RESULTS AND DISCUSSION

Result analysis of K Nearest Neighbour-based Linear Regression (KNN-LR) framework is discussed and compared with two existing methods. The compared existing methods areCompetence-enhanced and Maintenance Distance Vector (MC-DV) [1] and Security Fault Tolerant Routing (SFTR) [2]. KNN-LR framework conducts the performance analysis on the factors such as throughput, network lifetime, data loss rate and end to end delay for stable and consistent wireless network communication. The performance of KNN-LR framework is described with the help of tables and graphs.

4.1 Measure of Throughput

The throughput is defined as the ratio of data packets received at the fusion center 'DP_{FC}' to the data packets transmitted from the source sensor node 'DP_S'. It is measured in terms of kilo bits per second (kbps) and formulated as follows.

$$Throughput = \frac{DP_{FC}}{DP_S} \quad (16)$$

Table 1 Tabulation for Throughput

Data Packet size (KB)	Throughput (Kbps)		
	KNN-LR	MC-DV	SFTR
100	70	35	48
200	150	72	95
300	220	120	142
400	290	180	207
500	350	250	272
600	360	260	281
700	430	295	330
800	520	395	430
900	580	470	500
1000	630	520	550

Performance of throughput with respect to different data packet sizes from source node to base station is described in table 1. The data packet size of 100KB to 1000KB is considered. The throughput is significantly increased using KNN-LR framework when compared to existing MC-DV [1] and SFTR [2] methods. Simulation results of KNN-LR framework is shown in figure 5.

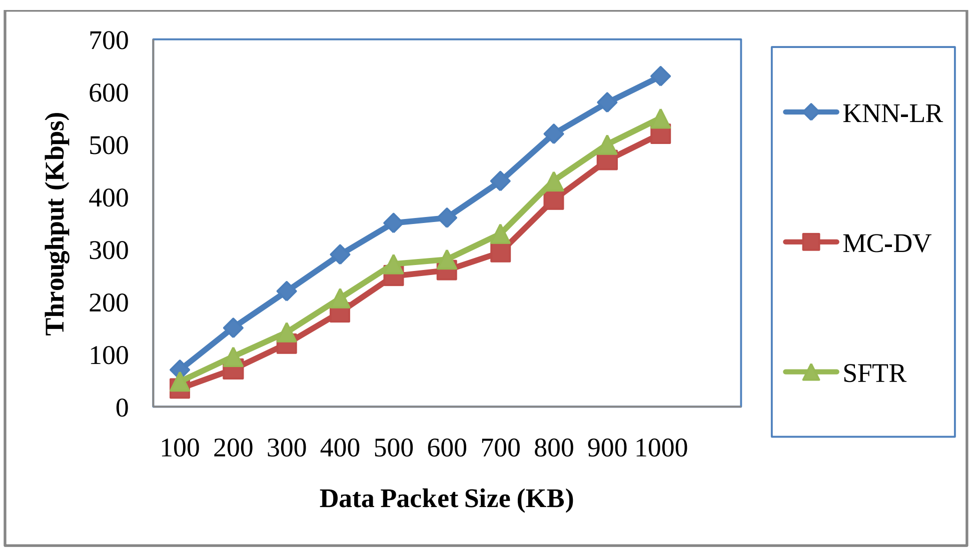

Figure 5 Performance measure of throughput

Figure 5 illustrates the simulation result of throughput with respect to varies data packet sizes. The throughput for data packet transmission is improved in proposed KNN-LR framework than other methods. With the application of integration rule and tally rule, both the local sensor and global sensor detection is made in a proficient manner. At first, the presence or absence of target node is separated by using local pivotal factor.Then, tally rule is used to obtain global pivotal factor along with a likelihood ratio to determine the sensor nodes for acceptance of the data packets.Both local and global pivotal factor is used by the fusion center for the selection of neighborhood sensor node to transmit data packets. This in turn helps to improve the throughput by 55% compared to MC-DV [1] and by 34% compared to SFTR [2] respectively.

4.2 Measure of Network Lifetime

The network lifetime is described as the ratio of total number of sensor nodes '$Total_{SN}$' in the network and the sensor node addressed '$SN_{addressed}$' for communication between sensor nodes. It is measured in terms of percentage (%).

$$NetworkLifetime = \left(\frac{SN_{addressed}}{Total_{SN}}\right) * 100 \qquad (17)$$

Table 2 Tabulation for Network Lifetime

Sensor Node	Network lifetime (%)		
	KNN-LR	MC-DV	SFTR
10	78.88	62.38	67.52
20	82.46	66.1	70.97
30	84.75	69.22	74.29
40	83.77	67.1	72.15
50	87.59	71.3	76.36
60	89.32	73.12	78.19
70	87.33	71.07	76.13
80	90.47	75.09	80.15
90	93.46	78.32	83.19
100	95.21	81.22	85.67

Table 3 describes performance of network lifetime with respect to different number of sensor node in network. To conduct experimental work, number of sensor nodes between 10 and 100 nodes is considered. Performance of network lifetime is improved using KNN-LR framework than the existing MC-DV [1] and SFTR [2] methods.

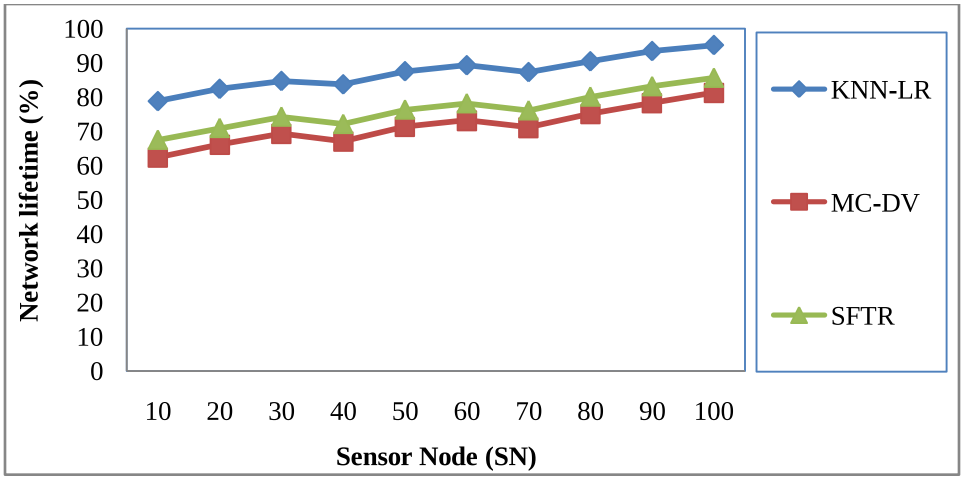

Figure 6 Performance measure of Network Lifetime

Figure 6 describes simulation results of network lifetime with different number of sensor nodes. As shown in figure, the network lifetime is considerably increased using KNN-LR framework than the existing methods. With the use of logistic regression model, network lifetime is increased. By applying regression model, the sensor nodes are identified with the help of threshold factor which send a data to fusion center. The sensor nodes whose likelihood ratio is only greater than the threshold factor gets chance for sending the data packets to fusion center. As a result, the network lifetime is improved during data packet transmission. From the result analysis, the network lifetime is improved by 18% compared to MC-DV [1] and by 14% compared to SFTR [2] respectively.

4.3 Measure of data loss rate

The measure of data packet lost during data transmission is defined as a data loss rate. It is measured based on the difference between sizes of data packet send and received. It is expressed in Kilo Bytes (KB) and it is given below.

$$DataLossrate = D_s(size) - D_r(size) \qquad (18)$$

From (18), 'D_s' and 'D_r' represents the size of data sent and received in WSN.

Table 3 Tabulation for data loss rate

Data Packet Size (KB)	Data loss rate (KB)		
	KNN-LR	MC-DV	SFTR
100	29	38	35
200	34	43	40
300	36	45	42
400	34	43	40
500	39	48	45
600	42	51	48
700	39	49	46
800	44	53	50
900	46	55	52
1000	47	57	54

Table 3 clearly shows an impact of data loss rate with respect to data packet size. Data packet size in the ranges from 100 KB to 1000 KB is considered. Data loss rate is reduced using KNN-LR framework when compared to existing MC-DV [1] and SFTR [2] methods respectively.

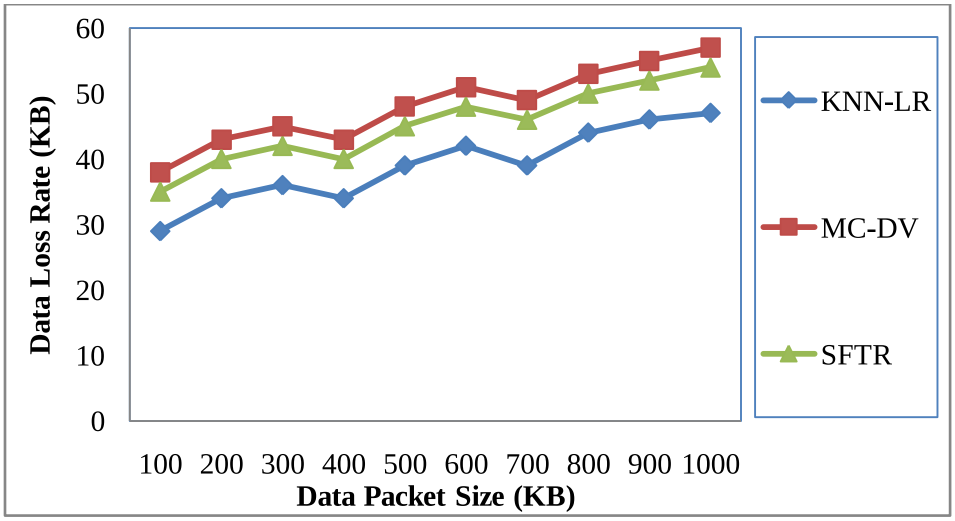

Figure 7 Performance measure of data loss rate

Figure 7 illustrates the simulation result of data loss rate with respect to data packet size to be sent. From the figure, it is clearly evident that the data loss rate is reduced in proposed KNN-LR framework by varying the data packet size.According to the link quality representation with the value of expected data packet acceptance ratio, optimal routing path is selected.By using the data packet acceptance ratio, active link quality is measured to send the information between two sensor nodes. Moreover, the link quality determines all available routes from the source sensor node to the fusion center.Based on different route path, data loss rate is minimized. Therefore, data loss rate is reducedby 19% compared to MC-DV [1] and by 14% compared to SFTR [2].

4.4 Measure of end to end delay

The end to end delay is illustrated as the measure of time taken by each sensor node to reach the destination during data packet transmission. Delay is measured in milliseconds (ms).

$$Endtoenddelay = (Expected_t - Actual_t) * Numberofpackets \quad (19)$$

From (19), ‘$Expected_t$’ and ‘$Actual_t$’ represents the expected and actual time for data delivery with respect to the number of packets.

Table 4 Tabulation for end to end delay

Number of packets	end to end delay (ms)		
	KNN-LR	MC-DV	SFTR
9	31.35	46.14	41.27
18	37.32	52.13	47.46
27	43.45	58.31	53.79
36	47.35	62.83	57.82
45	46.19	59.72	55.29
54	49.31	63.13	58.83
63	53.43	68.31	63.71
72	57.9	73.13	68.39
81	62.67	77.32	72.88
90	67.89	82.14	76.45

Table 4 describes performance of delay with respect to number of data being sent from source node. Performance of end to end delay is reduced using KNN-LR frameworkthan the existing MC-DV [1] and SFTR [2] methods. The simulation result of delay is shown in figure 8.

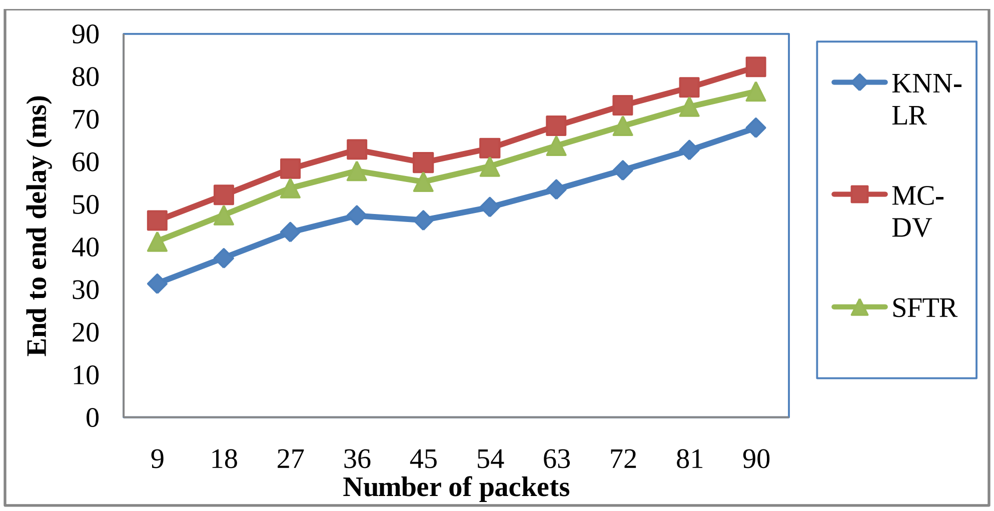

Figure 8 Performance measure of end to end delay

Figure 8 depicts the simulation result of delay with respect to number of data packets varied from 9 to 90. From the figure, it is clearly evident that the proposed KNN-LR framework reduces the delay during the data packet transmission between different source nodes. With the support of link quality factor, optimal route path is selected. Based on the density of the receiver and higher probability of successful reception, the end to end delay is reduced. According to the threshold factor, the fusion center performs data packet forwarding and sends the results to the destined node in WSN.As a result, end to end delay is reduced by 23% compared to MC-DV [1] and by 17% compared to SFTR [2] respectively.

V. RELATED WORKS

A link prediction algorithm was developed in [11] to illustrate the link failure difficulty. Using link prediction algorithm, end-to-end delay was reduced with minimum data packet drops. But link stability was not maintained effectively. Link Quality Estimation model in [12] establish the link quality in distributed grid environments. It measures the link quality affecting factor based on noise and path loss model. However, network throughput was not improved.

Heuristic artificial bee colony algorithm [13] provides optimized network consistency by selecting routing path and mobile sink path. Thus it improves network lifetime. However, consistency of the data was not improved. In [14], optimized hierarchical routing technique was presented to reduce energy consumption. But link stability remains unaddressed. Another Intercluster Ant Colony Optimization algorithm [15] was considered to enhance the network lifetime. But, IC-ACO failed in obtaining a stable route for data transmission.

VI. SUMMARY

A stable and consistent wireless network communication is provided by proposing a K Nearest Neighbour –based Logistic Regression (KNN-LR) framework.At first, stability-aware logistic regression model is used to obtained higher throughput and network lifetime. The local and global pivotal value is determined and thepresence or absence of target node is established with the aid ofMaximum conditional likelihood ratio.Next, link quality is used as a factor to measure the consistency in WSN. Here, optimal route is selected for data transmission based on the distance between sensor nodes. Thus, it minimizes the data loss rate and end to end delay ensuring consistency during wireless network communication

REFERENCES

[1] Shan lin, Gang zhou, Motaz al-hami, Yafengwu, John A. Stankovic, Tian he, Xiaobing WU and Hengchangliu, "Toward Stable Network Performance in Wireless Sensor Networks: A Multilevel Perspective", ACM Transactions on Sensor Networks, Volume 11, Issue No. 3, February 2015, Pages 42-68.

[2] Zhengwang Ye, Tao Wen, Zhenyu Liu, Xiaoying Song and Chongguo Fu," A security fault-tolerant routing for multilayer non-uniform clustered WSNs", EURASIP Journal on Wireless Communications and Networking, SpringerOpen, May 2016

[3] Pu Wang and Ian F. Akyildiz, "On the Stability of Dynamic Spectrum Access Networks in the Presence ofHeavy Tails", IEEE Transactions on Wireless Communications, Volume 14, Issue No. 2, February 2015, Pages 870-881.

[4] Enan A. Khalil and Bara'a A. Attea, "Stable-Aware Evolutionary Routing Protocol for Wireless Sensor Networks" Wireless Personal Communications, Springer, Volume 69, April 2013, Pages 1799–1817

[5] SenthilnathanPalaniappan and KalaiarasanChellan, "Energy-efficient stable routing using QoS monitoring agents in MANET", EURASIP Journal on Wireless Communications and Networking, Springer, Volume 2015,Issue no 13, December 2015, Pages 1-11.

[6] Nitin Mittal, Urvinder Singh and Balwinder Singh Sohi, "A stable energy efficient clustering protocol for wireless sensor networks", Wireless Networks, Springer, Volume 23, Issue No. 6, August 2017, Pages 1809–1821.

[7] Yi Chen, Xuan Wang and Lin Cai, "On Achieving Fair and Throughput-Optimal Scheduling for TCP Flows in Wireless Networks", IEEE Transactions on Wireless Communications, Volume 15, Issue No. 12, December 2016, Pages 7996- 8008.

[8] Jiao Zhang, FengyuanRen, Shan Gao, Hongkun Yang and Chuang Lin, "Dynamic Routing for

Data Integrity and Delay Differentiated Services in Wireless Sensor Networks", IEEE Transactions on Mobile Computing , Volume: 14, Issue no. 2, February 2015, Pages 328 – 343.

[9] Arun K. Kumar, Krishna M. Sivalingam and Adithya Kumar, "On reducing delay in mobile data collection based wireless sensor networks", Wireless Networks, Springer, Volume 19, Issue No. 3, April 2013, Pages 285–299.

[10] Xiaofeng Lang and Kwan-Wu Chin, "Algorithms for bounding end-to-end delays in Wireless Sensor Networks", Wireless Networks, Springer, October 2014, Volume 20, Issue No. 7, Pages 2131–2146.

[11] Anita Yadav, Y. N. Singh and R. R. Singh, "Improving Routing Performance in AODV with Link Prediction in Mobile Adhoc Networks", Wireless Personal Communications, Springer, Volume 83, Issue No. 1, July 2015, Pages 603–618.

[12] Wei Sun, Lu Wei, Jianping Wang, Daoming Mu, Qiyue Li and Xiaojing Yuan, "A Link Quality Estimation model of Wireless Sensor Networks for Smart Distribution Grid", IFAC-PapersOnLine, Volume 48, Issue No. 28, 2015, Pages 432-437.

[13] YinggaoYue, Jianqing Li, Hehong Fan and Qin Qin, "Optimization-Based Artificial Bee Colony Algorithm for Data Collection in Large-Scale Mobile Wireless Sensor Networks", Hindawi Publishing Corporation, Journal of Sensors, Volume 2016, 2016, Pages 1-12.

[14] Shaimaa Ahmed El-said, AsmaaOsamaa and Aboul Ella Hassanien, "Optimized hierarchical routing technique for wireless sensors networks", Soft Computing, Springer, Volume 20, Issue No. 11, November 2016, Pages 4549–4564.

[15] Jung-Yoon Kim, Tripti Sharma, Brijesh Kumar, G. S. Tomar, Karan Berry and Won-Hyung Lee, "Intercluster Ant Colony Optimization Algorithm for Wireless Sensor Network in Dense Environment", Hindawi Publishing Corporation, International Journal of Distributed Sensor Networks ,Volume 2014, 2014, Pages 1-10.