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Energy efficient Q learning based Kullback sparse encoder for traffic and congestion control data delivery in WSN

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Abstract

In dense traffic Wireless Sensor Network (WSN), traffic congestion can increase routing overhead and packet loss, which restricts the entire network performance, therefore a traffic-aware and congestion-control data delivery is required to control the traffic. The proposed Energy-efficient Q-learning and Kullback Sparse Encoder (EQ-KSE) method is used for traffic-aware routing and congestion-control data delivery method for WSN. The method enforces a traffic balancing strategy using the energy-efficient reward function and estimates the wireless link quality by the Energy-efficient and Q-Learning Routing algorithm. On the basis of the estimation of each wireless link, the Energy-efficient Q-Learning based Traffic-aware Routing model makes routing decisions through energy and queue length to reduce routing overhead and time significantly. With the obtained optimal routes data aggregation are performed at the sink node, causing a proportionate amount of congestion. To handle this issue, a Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery method is proposed. This KL-SAE model with the aid of the reconstruction loss function, through divergence reduces the congestion, therefore contributing to packet loss, and packet delivery ratio. Simulation results show that EQ-KSE method performs traffic-aware routing by minimizing both the route selection time and overhead. In high node density scenarios, it also betters the state-of-the-art methods in packet delivery ratio and packet loss rate.

Keywords: Wireless Sensor Network, Kullback Leibler, Sparse Auto Encoder, Traffic-aware, Congestion-control, Data Delivery.

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1. Introduction

WSN includes several sensors possessing with certain power supply, processing speed, sender and receiver. With the purpose of acquiring significant and predominant sensor data, the sensor nodes gather information from their adjacent nodes and convey them to a unified location. On the basis of the request made, unpredicted and associated information signals may be ushered to a reduced number of sinks. This in turn results in congestion that is packet collisions or overflowed buffer in the channel.

In WSN, sensors are connected in wireless manner potential for acquiring, processing and sensory data transmission efficiently. But, due to the open nature like dynamic topology and self-organizing structure, WSNs are found to be highly susceptible to congestion issue, leading to enhance packet loss ratio, higher delay and lesser throughput. In order to overcome this problem, Fuzzy Sliding Mode Congestion-control FSMC method is proposed in [14].

Initially, signal-to-noise ratio of TCP model, called new cross-layer congestion control among transmission layer and MAC layer is presented. Followed by which, With Sliding Mode Control (SMC), fuzzy control are integrated which are called as fuzzy sliding mode controller (FSMC) is structured. With this structural design, buffer queue size was supervised in an adaptive manner in congested nodes and hence minimized the influence of extraneous unknown interference. Owing to this FSMC efficiently adapted to lesser average delay, low packet loss ratio and better throughput.

In order to provide energy efficient transmissions, an Adaptive Weight Firefly Congestion Control (AWFCC) was proposed in [16]. In AWFCC, rate-based congestion control based on cluster routing was designed to minimize the consumption of energy entire network. Initially, clustering of nodes was performed by means of hybrid K-means and Greedy best first search algorithms.

Followed by which, rate control was analyzed by employing firefly optimization, therefore ensuring high packet delivery ratio. Finally, packets were transmitted with increased throughput by means of Ant Colony Optimization-based routing. Owing to this mechanism, delay and consumption of energy is reduced with higher packet delivery and reliability.

To overcome this challenge, the energy-efficient, traffic-aware routing with congestion-control data delivery method to boost the network performance. The contributions of this work are given below,

- The efficient traffic-aware routing and congestion control data delivery congestion avoidance approach using Kullback Leibler Sparse Auto Encoder (KL-SAE) by considering important constraints of WSN namely energy, queue length, packet loss rate, and packet delivery ratio wireless sensor networks is proposed.

- Energy-efficient Q-Learning based Traffic-aware Routing has been applied in search of traffic aware routes. The reward functions in Q-learning estimates both the energy consumption and queue length during routing between source and sink node, energy of link, queue length, packet loss rate, and packet delivery ratio.

- Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery model is used to perform data delivery by controlling the congestion occurring during data aggregation in WSN. The optimal route is the best route among multiple optimal routes identified by SAE in terms of routing overhead, routing time, packet loss rate and packet delivery ratio. The SAE considers data packet loss probability on various alternate routes exposed via Kullback Leibler function for efficient data delivery.

- Lastly, proposed KL-SAE method is compared with the state-of-the-art methods.

The paper is summarized as: Section 2 describes literature review related to traffic-aware routing with congestion-control data delivery. In Section 3, Energy-efficient Q-learning and Kullback Sparse Encoder (EQ-KSE) method is explained which comprise network model followed with traffic-aware routing and congestion-control data delivery model. In Section 4, proposed method EQ-KSE is discussed. Section 5 illustrates conclusion of this paper.

2. Related works

Current technology development in WSNs has led the way to a rapid expansion in certain applications like, health care, progression automation and so on. Such applications necessitate data packets transmitted in authentic manner and minimum delay. Hence, data delivery via WSN has seen a spectacular improvement in the earlier decade and is anticipated to carry on with the same inclination.

An end-to-end congestion control algorithm with the objective of ensuring high throughput and low latency to address the congestion control was proposed in [7]. Yet another energy efficient algorithm employing intelligent fuzzy rules in the domain of agriculture was designed in [13]. The fuzzy inference system used here were employing in making significant routing decisions.

In the recent few years, WSNs have bestowed a novel technological vision owing to its extensive development in wireless communication, network protocols, self-configuration nature and ubiquitous type of computing. Sensor nodes perform significant data transmission between the sources and sink via reactive, proactive, or hybrid routing protocol.

The time sensitive applications in WSN necessitate energy-efficient and reliable data transmission with constrained resource availability. To address these issues an optimal cluster head selection method was proposed in [1] to select the node as the cluster head with the purpose of reducing end-to-end delay and congestion index during data delivery. Yet another method to address congestion called, Dynamic Alternate Buffer switching and Congestion Control was designed in [17] based on remaining buffer and energy, therefore reducing data loss ratio. WSN guaranteeing involving throughput, latency and lost packets were addressed in [15].

There has been an extensive research effort made on the management of traffic utilizing WSNs for energy optimization and to ensure efficient data delivery. Many researches direct to consider MAC protocols that necessitate optimization of energy and allocating the data packets on a priority fashion. Moreover, data delivery management is also contemplated as the challenging issue to enhance the quality of service (QoS).

An energy-efficient geographic routing model to deal with load balancing and therefore enhancing the network lifetime is designed in [12]. In order to construct efficient data transmission in WSN, improved ant colony optimization algorithm is proposed. With this the energy consumption is said to be minimized in an extensive manner, therefore extending the network lifetime. An adaptive medium access control mechanism is designed in [5] where the nodes are split into groups for traffic rate and transmission of delay.

As the sensor nodes in WSN are found to be positioned in a dense manner to shield the target are entirely, a small portion of data redundancy is said to occur, therefore causing congestion. To address this issue, Congestion Control Fuzzy Decision method is developed in [8] for distributing network traffic through optimal paths. With this energy consumption between nodes were said to be balanced and therefore enhancing the routing service quality. In [18], a novel data aggregation method was proposed on the basis of node clustering and extreme learning machine (ELM) that in turn significantly minimized the redundant and erroneous data significantly. A routing algorithm based on congestion control called CCOR was proposed in [6] to minimize packet loss rate for WSN. Three parameters, distance between sender and receiver, relative success rate and node buffer occupancy were utilized in [2] to define utility function with which congestion was said to be detected, contributing to minimum energy and maximum throughput.

Yet another Priority-based Congestion-avoidance Routing protocol for heterogeneous WSN was elaborated in [3] to concentrate on network throughput and energy consumption. A comprehensive data gathering model focusing on energy consumption called, Comprehensive Visual Data Gathering Networking Architecture was presented in [19].

An efficient data delivery method based on the multi-perceived domain that in turn integrated communities concerning correlation degree of nodes [11] and new communities also aid in transmitting the data in an extensive manner. Multi-path management scheme supporting sink mobility therefore corroborating to reliability and energy efficiency was proposed in [10]. Redundant traffic was handled in [9] by employing zone-based routing.

Based on the above materials and methods, we have identified a more efficient method to address the issues related for improving data packets efficiency and reducing routing overhead and time in WSN by employing Energy-efficient Q-learning and Kullback Sparse Encoder (EQ-KSE) method. The elaborate description of the EQ-KSE method is provided in the following sections.

3. Energy-efficient Q-learning and Kullback Sparse Encoder (EQ-KSE) method

In this section, a data delivery method is developed on the basis of the newly designed traffic-aware routing and congestion-control factors. The objective of this method is to develop a data delivery method in WSNs using the deep learning algorithm. The proposed method undergoes two phases for providing data delivery, which includes traffic-aware routing and congestion-control model. Figure 1 shows the block diagram of EQ-KSE method.

From figure 1, the sensor node simulation is done in the network. To initiate the routing process, the optimal routs are selected based on the energy consumption and queue length and substituted to the reward function in Q-learning model. Thus, for optimal route selection, an Energy-efficient and Q-Learning Routing algorithm is utilized. After the selection of optimal routes, congestion-control data delivery model is designed using Kullback Leibler loss function. Thus, the robust data delivery method is performed based on the proposed method, Energy-efficient Q-learning and Kullback Sparse Encoder (EQ-KSE).

3.1. Network model

In WSN "n'', sensor nodes are positioned with network size of "A'' for traffic-aware and congestion control data delivery. WSN illustrated in graph $G = \{V, E\}$ where $V = \{V_1, V_2, ..., V_n\}$ denotes a set of vertices and "$E = \{E_1, E_2, ..., E_n\}''$ represents set of associating edges among sensors. "V_n'' can be examined as sink node possessing sufficient energy resource as illustrated in figure 2.

As shown in the above proposed network model, also En_i, where $i = 1, 2, ..., n$ represents the initial sensor energy,D_i denoting the delay. Data packets DP are transmitted by source sensor node V_i to the sink node V_n, then overall energy decreases during each transmission and data packet reception. Then, $En(T)$ and $En(R)$ denotes the energy consumed during transmitting and receiving i bits of data packets DP through source sensor node V_i to sink node V_n respectively and this is mathematically formulated as given below.

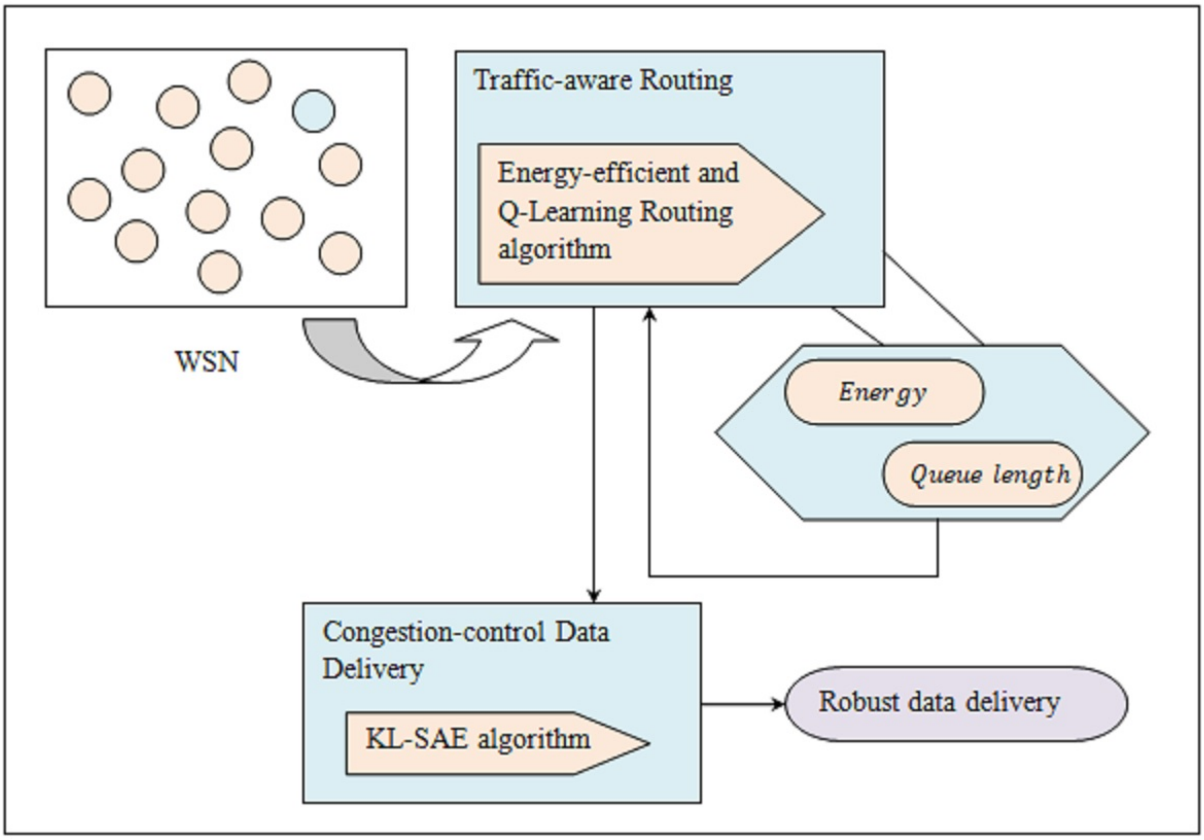

Figure 1: Block diagram of EQ-KSE method

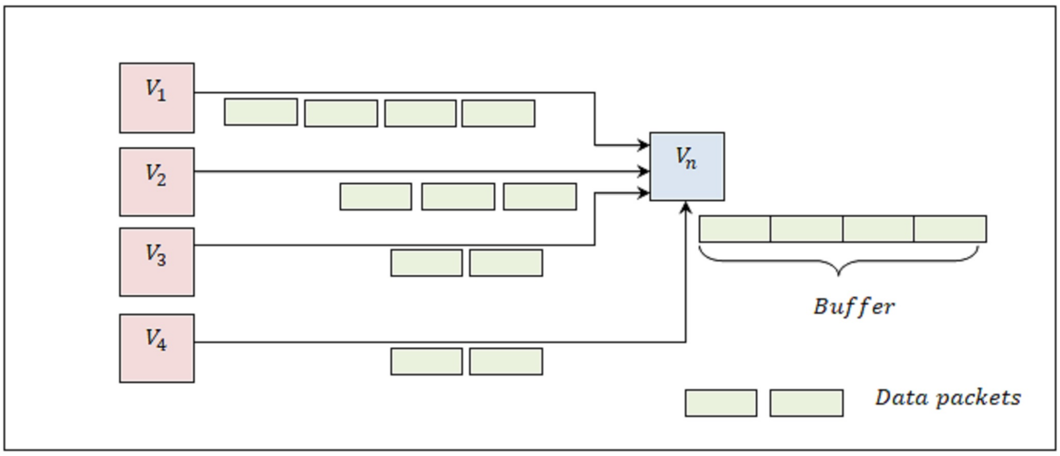

Figure 2: Proposed Network Model

$$En(T) : V_i \to V_n = i(En(d) + En(amp) * Dis^2) \tag{3.1}$$

$$En(R) : V_i \to V_n = i[En(d)] \tag{3.2}$$

From the above equations (3.1) and (3.2), $En(T), En(R)$ represents the energy consumed during the transmission and reception of single data packets. Moreover, $En(amp)$ and $En(d)$ denotes the energy being amplified during data packet transmission and energy dissipation rate involved during data packet transmission and reception respectively. Finally, Dis^2 symbolizes the distance between the source sensor nodes V_i and sink node V_n. Then, the total energy consumed is mathematically formulated as given below.

$$En(Tot) = En(T) + En(R) \tag{3.3}$$

With the above network consideration, the proposed Energy-efficient Q-learning and Kullback Sparse Encoder (EQ-KSE) method is aimed at designing traffic-aware congestion control by identifying optimal alternate route for data delivery in WSN.

3.2. Energy-efficient Q-Learning based Traffic-aware Routing

Varying from the conventional model perspective for traffic-aware routing, Machine Learning-based routing can encapsulate the heightening complication and adjust to changes in network infrastructure in consequence. Nevertheless, comprehensive data packet control for ML has been an ultimatum in the prevailing distributed framework. This is why an Energy-efficient Q-Learning based Traffic-aware Routing (EQL-TR) is proposed. Figure 3 shows the structure of Energy-efficient Q-Learning based Traffic-aware Routing model.

As shown in the above figure, the EQL-TR is based on four tuples (S, A, RTP, R), where S denotes the set of states, A the set of actions, RTP representing the route transition probability matrix and R finally representing the reward. The framework of the EQL-TR model comprises of sensor nodes data packets flowing in WSN from a source to the destined destination. The presence of a given data packet DP at sensor node SN_i corresponds to the state of that data packet at time instance t as s_i^t. Next, an action $A^t_{SN_iSN_j}$ corresponds to a decision made by the agent Ag to forward the data packet from sensor node SN_i to the adjacent node SN_j appropriated by the policy $Pol(s_i^t)$ managing route transition probability matrix as formulated below.

$$Pol(s_i^t) = argmin\ Q\left(s_i^t, A^t_{SN_iSN_j}\right) \tag{3.4}$$

Based on the resultant value from the above equation (3.4), the state of data packet DP will move from $S^t_{SN_i}$ to $S^t_{SN_j}$ and the accompanying reward with the action will be executed, ensuring efficient traffic-aware routing. Next, in the EQL-TR model, the action-value $Q_{t+1}(S_t, A_t)$ is updated on the basis of the following equation.

$$Q_{t+1}(S_t, A_t) = (1 - \alpha) * Q_t(S_t, A_t) + \alpha * [R_t + \min(S_{t+1}, A)] \tag{3.5}$$

From the above equation (3.5), α corresponds to the learning rate to control the change occurring in the Q-table. Initially, the states and actions of the corresponding Q-values are initialized to zero and its values will be changed according to the rewards respectively. Each sensor nodes data packet is an agent and the sensor node that contains the data packet is contemplated as the state of the agent. For the EQL-TR model, a set of parameters that represent the sensor node to be utilized by the agent is defined. For a sensor node, let a sensor node SN_i the parameters are as follows,

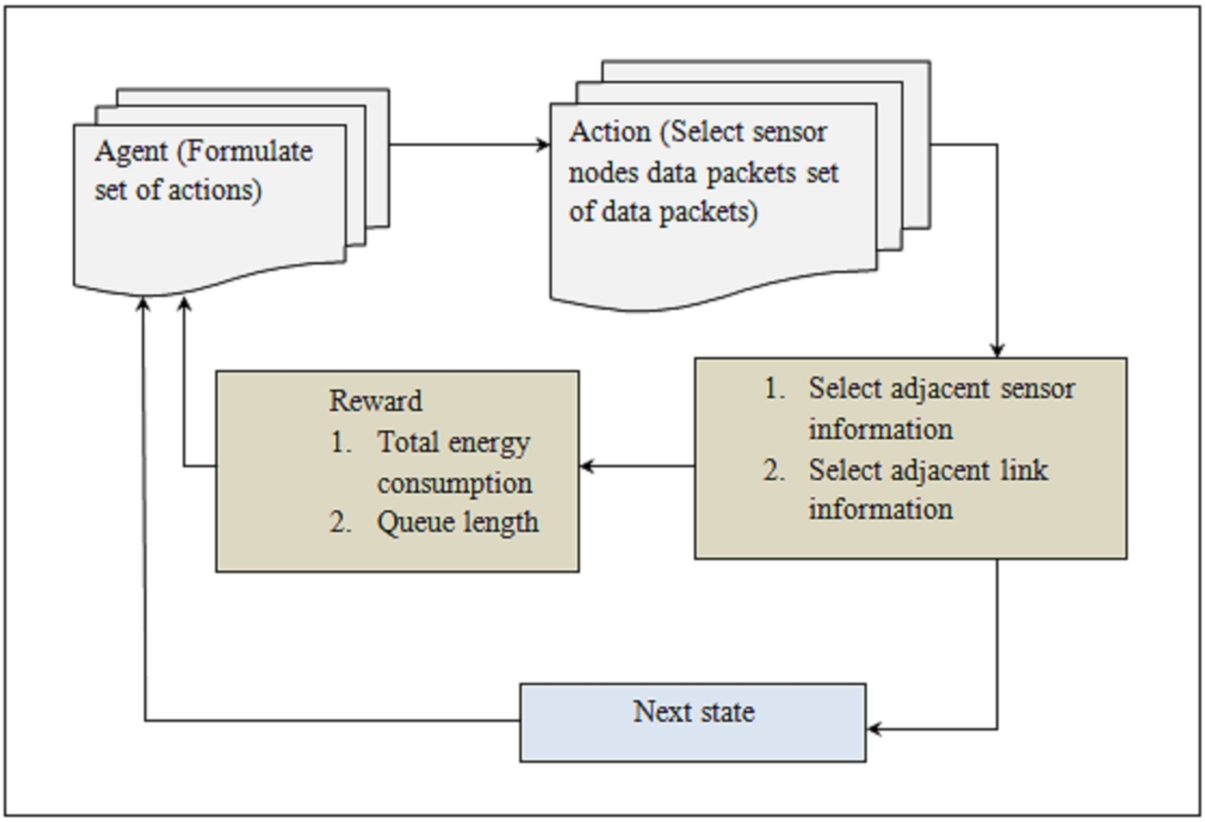

Figure 3: Structure of Energy-efficient Q-Learning based Traffic-aware Routing

the queue length of sensor node SN_i and the energy consumption of sensor node SN_i. On basis of measure values, parameters are measured as follows.

$$Q \sum_{i=1}^{n} SN_i = \sum_{i=1}^{n} \frac{Buff[DP_i]}{Buff_{size}[SN_i]} \tag{3.6}$$

From the above equation (3.6), the queue length Q of sensor node SN_i is measured on the basis of the data packets in the buffer $Buff[DP_i]$ and the size of the buffer $Buff_{size}$ at sensor node SN_i respectively. Now, the traffic loading gradient at node SN_i or the reward is mathematically formulated as given below. The reward function used by the agent is designed on the basis of two measured parameters. In other words, the reward is proportional to the queue length and the total energy consumption. In addition to the two parameters, two tuning parameters ω_1 and ω_2 are utilized and mathematically formulated as given below.

$$R = \omega_1[En(Tot) \sum_{i=1}^{n} SN_i] + \omega_2[Q \sum_{i=1}^{n} SN_i], \omega_1, \omega_2 \in [0,1] \& \omega_1, \omega_2 = 1 \tag{3.7}$$

From the above equation (3.7), the reward R, is measured on the basis of queue length Q and the total energy consumption $En(Tot)$ at the respective sensor node SN_i tuning weights ω_1, ω_2. Based on the resultant value of the reward, either the route is selected or process is said to be continued with other routes. The pseudo code representation of Energy-efficient and Q-Learning Routing is given below.

As given in the above Energy-efficient and Q-Learning Routing algorithm, the objective remains in obtaining the route with minimum route selection time and route overhead. To attain this objective,

Input: Sensor nodes '$SN = (SN_1, SN_2, \dots, SN_n)$', Data Packets '$DP = (DP_1, DP_2, \dots, DP_n)$', sink node '$V_n$'

Output: Energy-efficient traffic-aware route '$R_1, R_2, \dots, R_n$'

Step : Initialize energy amplification rate '$En(amp)$', energy dissipation rate '$En(d)$'

Step 2: Initialize distance 'Dis^2', learning rate 'α'

Step 3: Initialize data packets in buffer '$Buff[DP_i]$', size of buffer '$Buff_{size}$'

Step 4: Begin

Step 5: For each Sensor nodes 'SN' with Data Packets 'DP' and sink node 'V_n'

Step 6: Formulate energy consumed during the transmission and reception as in equation (1) and (2)

Step 7: Measure total energy consumption as in equation (3)

Step 8: Formulate policy managing route transition probability matrix as in equation (4)

Step 9: Formulate action-value as in equation (5)

Step 10: Measure queue length as in equation (6)

Step 11: Estimate reward as in equation (7)

Step 12: Return (traffic-aware routes)

Step 13: End for

Step 14: End

Figure 4: Algorithm 1 Energy-efficient and Q-Learning Routing

first, the parameters to be analyzed for reward function are the energy consumption and the queue length involved. With these two parameters analyzed during routing at the sink node between source and destination, the reward functions are measured and selected with the optimal route accordingly. With this the route selection time is said to be reduced as only with the successful consideration of the two parameters, routes are arrived at. Followed by which, optimal route via action-value function is identified without the necessity of admin as the values are stored in the Q-table, therefore contributing to routing overhead.

3.3. Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery model

Upon successful identification of the optimal route, the next step remains in aggregating the data or performing data aggregation for significant data delivery in WSN. Data aggregation refers to the process of integrating the data packets in an energy efficient manner. With optimal route identification all the sensor nodes involved in data delivery usually uses the same route and therefore resulting in congestion. Moreover, congestion in WSNs is inevitable where data traffic are said to be elevated to collection magnitude of channel. Buffer overflow eventually releases packets of data, minimizes packet delivery ratio, and finally compromising network throughput.

In this work, a novel Kullback Leibler Sparse Auto Encoder (KL-SAE) model for congestion-control data delivery in WSN. Figure 5 shows the structure of KL-SAE model. The conventional Sparse Auto Encoder includes three distinct layers, such as input layer, hidden layer and output layer. With the objective of attaining optimality in hidden layer or in other words to minimize the reconstruction error, a sparsity function employing Kullback Leibler (KL) function is introduced in the work. By applying this KL function, the data packet loss during data aggregation and data delivery in WSN is significantly reduced, therefore contributing to lower packet loss rate with higher packet delivery ratio. KL-SAE procedure can be divided into encoding and decoding.

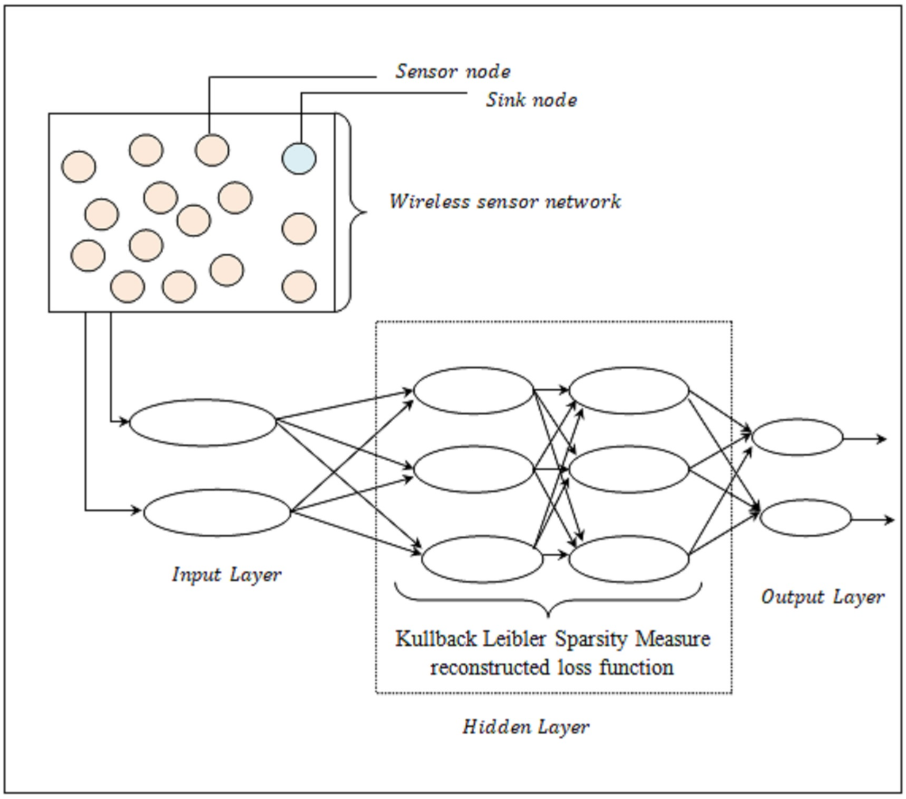

Figure 5: Structure of Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery model

As shown in the above figure, the encoding process is to acquire congestion-control data delivery $Q = [DP_1, DP_2, DP_3, ..., DP_n]^T$ of the input layer value R. The original user requirement data is denoted as $R = [R_1, R_2, R_3, ..., R_n]^T$ with n representing the total number of optimal routes being identified for data packet delivery or data delivery. Data delivery can be formulated by

$$Q = f(R) = \delta(WR + b) \tag{3.8}$$

From the above equation (3.8), vector $Q = [DP_1, DP_2, DP_3, ..., DP_n]^T$ has represented the data packet feature expression of hidden layer, and parameter n corresponds to the sensor nodes data packets of the hidden layers. Moreover b represents the bias vector and W denotes the weight matrix between input and hidden layer and $\delta(R)$ corresponds to activation function.
Followed by which the decoding process is performed to acquire the reconstructed vector P of the output layer from the hidden layer value Q. This is formulated as given below.

$$P = g(Q) = \delta(W^T Q + b') \tag{3.9}$$

From the above equation (3.9), $P = [P_1, P_2, P_3, ..., P_n]^T$ and Q represents the data packet feature expression of output layer with b' denoting the bias vector. In the KL-SAE congestion-control data packet delivery process, with purpose of minimizing packet loss rate of data caused by data aggregation, the fundamental necessity is that the reconstructed vector output should be proximate to the input vector. In the process of constructing the data packet loss function, a sparsity measure employing Kullback Leibler (KL) function is added to the objective function of the encoder to achieve quality of service namely, congestion-free end-to-end data packet delivery.
The packet feature expression of hidden layer learned in this manner is not merely recurrent input.

Input: Sensor nodes '$SN = (SN_1, SN_2, \dots, SN_n)$', Data Packets '$DP = (DP_1, DP_2, \dots, DP_n)$', sink node '$V_n$'

Output: Congestion-control Data Delivery

step 1: Initialize route '$R_1, R_2, \dots, R_n$', weight matrix between input and hidden layer 'W', bias vector 'b', sparsity control factor 'β', regularization factor 'λ'

Step 2: Begin

Step 3: For each Sensor nodes 'SN' with Data Packets 'DP' and sink node 'V_n'

Step 4: Formulate encoding to obtain congestion-control data delivery of the input layer as in equation (8)

Step 5: Formulate decoding to obtain reconstructed vector as in equation (9)

Step 6: Measure Kullback Leibler Sparsity Measure reconstructed loss function as in equation (10)

Step 7: Return (congestion-control data delivery)

Step 8: End for

Step : End

Figure 6: Algorithm 2 Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery

On the other hand, the part of the Kullback Leibler Sparsity Measure in the hidden layer is to tackle congestion through the number of activated neurons or the sensor nodes involvement in WSN while performing data aggregation. The Kullback Leibler Sparsity Measure reconstructed loss function is mathematically formulated as given below.

$$L = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{1}{2}(Q_i - P_i)^2\right] + \frac{\lambda}{2}\sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij}^2 + \beta[\gamma_{spar}] \tag{3.10}$$

From the above equation (3.10), the reconstructed loss function L involves the average mean square error between reconstructed vector output and input $\frac{1}{2}(Q_i - P_i)^2$, regularization factor λ controlling overfitting (i.e., acceptance of large amount of sensor nodes data packets for aggregation at sink node) via weight W_{ij}, the Kullback Leibler Sparsity Measure γ_{spar} and finally, the sparsity control factor β respectively. Finally, the Kullback Leibler Sparsity Measure γ_{spar} is mathematically expressed as given below.

$$\gamma_{spar} = \sum_{i=1}^{k} SM \log\left(\frac{SM}{SM_i}\right) + (1 - SM)\log\left(\frac{1 - SM}{1 - SM_i}\right) \tag{3.11}$$

From the above equation (3.11) SM represents the sparsity measure and k corresponding to total amount of sensor nodes at specific instance ready for data aggregation respectively. With this, congestion-control data aggregated delivery process is ensured with minimum packet loss and maximum packet delivery ratio. The pseudo code representation of Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery is given below.

As given in the above Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery algorithm, the objective remains in reducing the data packet loss rate and improving the packet delivery ratio. To achieve this objective, a Kullback Leibler Sparsity Measure is introduced in the reconstructed loss function while modeling KL-SAE. By introducing this Kullback Leibler Sparsity Measure, it assists in estimating how much data packet loss occurs during the aggregation

Table 1: Simulation parameters settings

Simulation parameters	Values
Network Simulator	NS2.34
Simulation area	1200 m * 1200 m
Number of sensor nodes	50,100,150,200,250,300,350,400,450,500
Number of data packets	30,60,90,120,150,180,210,240,270,300
Mobility model	Random Waypoint model
Nodes speed	0 – 25 m/s
Simulation time	400sec
Routing Protocol	DSR
Number of runs	10

process at the sink node. By minimizing this error occurring at the buffer, congestion is said to be controlled, therefore contributing to both packet loss rate and packet delivery ratio concurrently.

4. Simulation setup

The simulation of the Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery method and existing methods namely Fuzzy Sliding Mode Congestion-control (FSMC) [1] and Adaptive Weight Firefly Congestion Control (AWF-CC)[2] are carried out by NS2.34 network simulator. Simulations are conducted with 500 sensor nodes distributed in squared area ($1200m * 1200m$) using Random Waypoint model. The sensor nodes travel in network with a speed of 0 to $25m/sec$. The total simulation time is $400sec$. In WSN, Dynamic Source Routing (DSR) protocol is implemented for traffic-aware with congestion-control data delivery. Table 1 represents simulation parameters.

4.1. Performance analysis of routing overhead

The first parameter of significance for traffic-aware routing is the routing overhead. During routing development for managing congestion or controlling the congestion at the sink node, a small amount of overhead is said to occur. The routing overhead is measured as given below.

$$RO = \sum_{i=1}^{n} SN_i * Mem[R] \tag{4.1}$$

From the above equation (4.1), the routing overhead RO is measured based on the sensor node involved in the simulation SN_i and the memory consumed during the identification of optimal routes $Mem[R]$ for data delivery. It is calculated in kilo bytes (KB). Table 2 describes routing overhead results of three different methods, KL-SAE, FSMC [1] and AWFCC [2].

Figure 7 given above portrays the routing overhead analysis results for 500 different sensor nodes considered for simulation. Figure 7 shows a direct relationship between sensor nodes and the routing overhead, meaning that the higher the sensor nodes involved in the simulation, the higher the routing overhead. The proposed method outperformed the other state-of-the-art methods [1] and [2] in this work and offered higher data delivery efficiency. Figure 7 explains proposed method of traffic which

Table 2: Routing overhead analysis using KL-SAE, FSMC [1] and AWFCC [2]

Number of sensor nodes	Routing overhead (KB)		
	KL-SAE	FSMC	AWFCC
50	100	150	200
100	200	300	400
150	300	450	600
200	400	600	800
250	500	750	1000
300	600	900	1200
350	750	1100	1450
400	800	1200	1600
450	900	1350	1800
500	1000	1500	2000

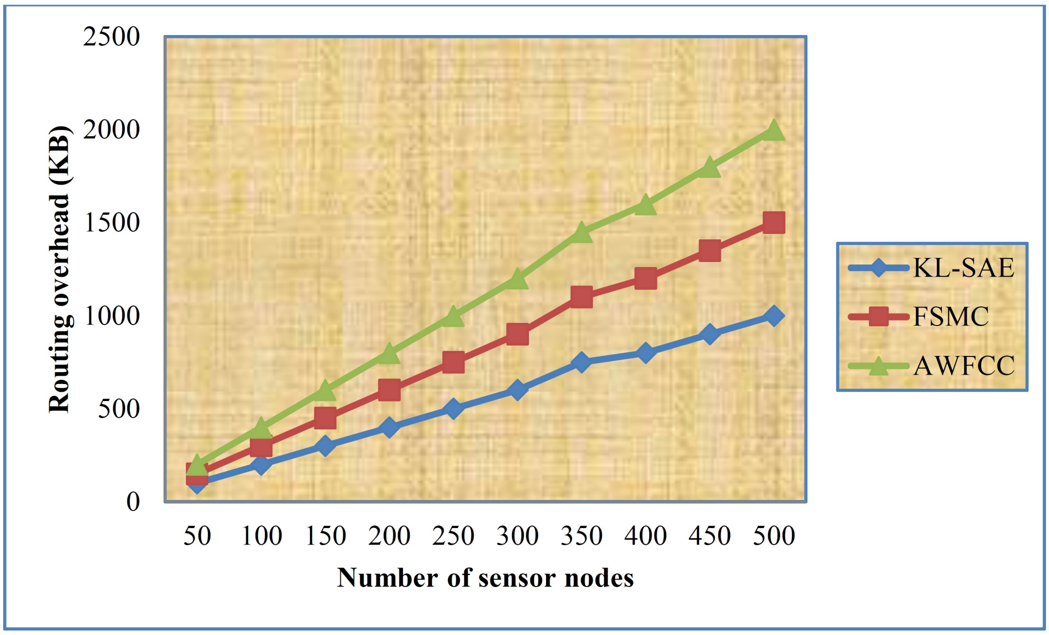

Figure 7: Graphical representation of routing overhead

Table 3: Routing time analysis using KL-SAE, FSMC [1] and AWFCC [2]

Number of sensor nodes	Routing time (ms)		
	KL-SAE	FSMC	AWFCC
50	10.75	11.5	12.25
100	15.35	25.35	35.35
150	21.25	31.55	42.35
200	25.55	40.15	58.05
250	31.45	55.25	70.35
300	40.35	63.15	90.25
350	55.25	71.35	105.5
400	68.35	89.05	125.35
450	71.55	105.83	140.15
500	93.15	125.34	155.35

identifies optimal route utilizing energy consumption and queue length as a reward for each node. Traffic-aware route management and optimal route selection based on two significant parameters facilitate the network traffic, which in turn reduces the routing overhead between source and sink node. Accordingly, obtaining stable routes, maintaining quality routes and eliminating low-quality routes via parameter analysis from the route can reduce overhead as much as possible. As a result, the routing overhead using KL-SAE is minimized as 33% compared with KL-SAE, FSMC and 50% compared with AWFCC respectively.

4.2. Performance analysis of routing time

Routing time or time involved in identification of routing in the presence of high traffic during the process of data aggregation in WSN. It is computed as follows,

$$RT = \sum_{i=1}^{n} SN_i * Time(R) \tag{4.2}$$

From the above equation (4.2), the routing time RT is measured based on the sensor node involved in simulation SN_i and the time consumed in routing $Time(R)$ It is calculated in milliseconds (ms). Table 3 describes routing time analysis results collected over different time intervals and between different source and sink node using three distinct methods, KL-SAE, FSMC [1] and AWFCC [2].

Figure 8 given above illustrates the routing time results using three different methods, KL-SAE, FSMS [1] and AWFCC [2] respectively. From the figure x axis refers to the distinct numbers of sensor nodes ranges from 50-500 used for simulation analysis at different time instances. Also y axis denotes the running time measured in terms of milliseconds. Moreover, the routing time is found to be directly proportional to sensor nodes. In other words, increasing sensor nodes causes an increase in the optimal route identification and therefore causing an increase in the routing time. However, simulations performed with 500 sensor nodes, the time consumed in routing using KL-SAE is observed to be 10.75ms, 11.5ms and 12.25ms using [1] and [2] respectively. From result analysis, optimal route identification employing KL-SAE is lesser compared with KL-SAE, FSMC and AWFCC. The enhancement was due to function of Energy-efficient and Q-Learning Routing algorithm. By utilizing this algorithm, energy consumption and queue length involved in analyzing

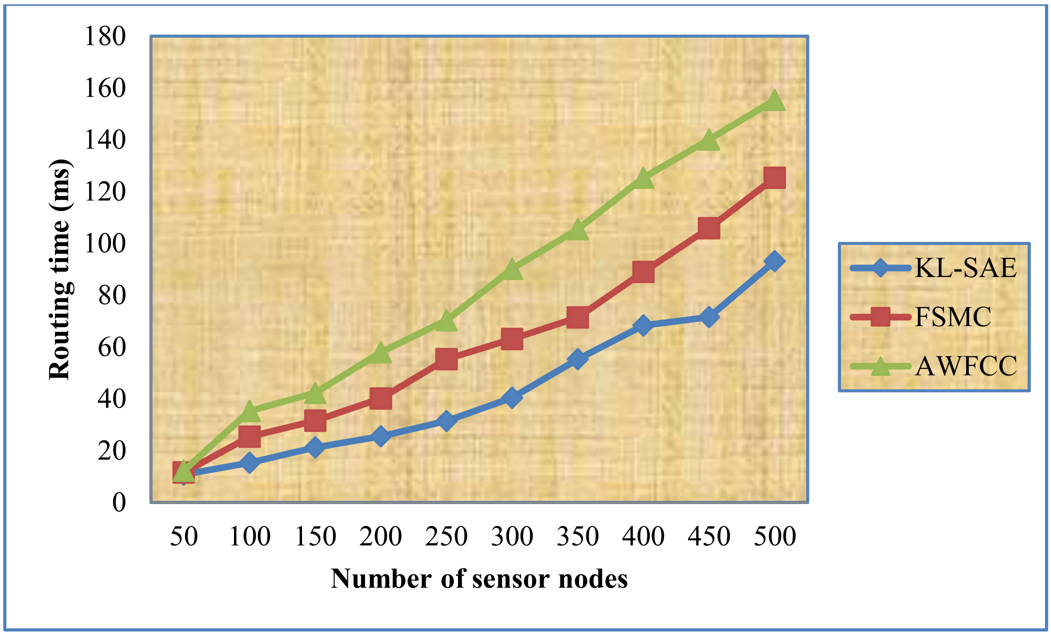

Figure 8: Graphical representation of routing time

the route is observed. With these two parameters reward function measurements are made following which optimal route are selected. As a result, the route selection time is found to be considerably minimized by 30% compared with KL-SAE, FSMC and 47% compared with AWFCC respectively.

4.3. Performance analysis of packet loss rate

Packet loss rate is referred as performing data aggregation at sink node, significant amount of congestion is occurred. It is measured by,

$$PLR = \frac{DP_l}{DP_s} * 100 \tag{4.3}$$

From the above equation (4.3), packet loss rate PLR is measured which depends on data packet lost DP_l and data packet sent DP_s. It is calculated in percentage (%). Table 4 given below lists the packet loss rate using three different methods, KL-SAE, FSMC [1] and AWFCC [2].

While data packets are transmitted in WSN, data packet loss is taken place due to several factors, like, loss in signal, congestion and irrelevant route identification. As such, materials and methods more aware of a sensor node, route and queue length can moreover minimize the packet loss rate. Section 3 describes proposed method of congestion-control is addressed through reconstructed loss function regularization factor and sparsity control factor. Figure 9 shows test results. With data packets sent by source node to sink ranges from 30-150 an increasing trend is observed and found to decline between 150 and 180 packets and so on. Therefore, neither increase nor decrease of packet loss rate was observed using the three methods. However, simulation analysis has showed an improvement with 30 data packets resulting in loss of 3, 4 and 5 data packets using the three methods. So, the overall packet loss rate is observed to be 10% using KL-SAE, 13.33% using [1] and 16.66% using [2] respectively. The improvement was due to the incorporation of Kullback Leibler Sparse Auto Encoder (KL-SAE) Congestion-control Data Delivery algorithm. By applying this algorithm, Kullback Leibler Sparsity Measure was used to obtain reconstructed loss function, therefore addressing sparsity and packet loss rate is minimized by 19% compared with KL-SAE, FSMC and 33% compared with AWFCC.

Table 4: Packet loss rate analysis using KL-SAE, FSMC [1] and AWFCC [2]

Number of data packets	Packet loss rate (%)		
	KL-SAE	FSMC	AWFCC
30	10	13.33	16.66
60	10.25	13.85	17.15
90	10.55	14	17.35
120	11	14.25	18
150	11.35	14.55	16.35
180	10	12.15	15
210	10.25	12	14.835
240	10	11.85	14
270	10.85	12.25	14.25
300	11.35	13	15.55

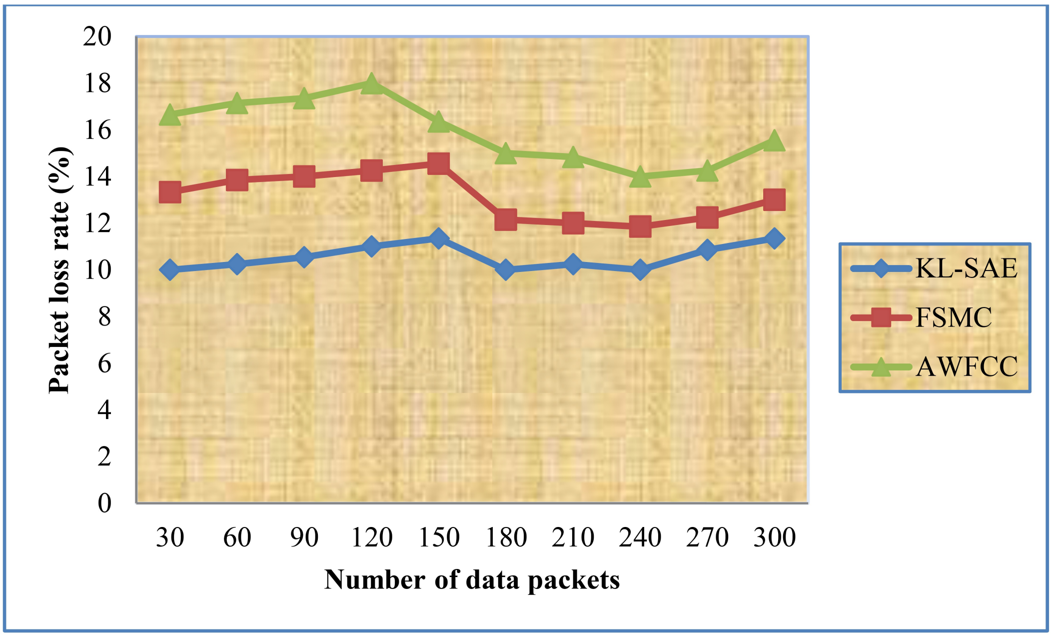

Figure 9: Graphical representation of packet loss rate

Table 5: Packet delivery ratio using KL-SAE, FSMC [1] and AWFCC [2]

Number of data packets	Packet delivery ratio (%)		
	KL-SAE	FSMC	AWFCC
30	86.66	83.33	80
60	90.15	87.15	85.25
90	93.25	90.35	88.15
120	91.45	88.25	85.35
150	92.25	89	86.75
180	90.15	86.35	84.25
210	92.35	89.15	85.15
240	91.45	87.25	84
270	92.35	89.35	86.75
300	91.55	87	85

4.4. Performance analysis of packet delivery ratio

Packet delivery ratio is estimated to measure performance of the proposed method. This is mathematically formulated as given below.

$$PDR = \left[\frac{DP_d}{DP_s}\right] * 100 \tag{4.4}$$

From the above equation (4.4), Packet delivery ratio PDR is measured which depends on data packet delivered DP_d and data packet sent DP_s at a particular time instance. Packet delivery ratio is calculated in percentage (%). Table 5 provides packet delivery ratio by applying different methods, KL-SAE, FSMC [1] and AWFCC [2] which are given below.

In figure 10, graphical analysis of packet delivery ratio with 300 dissimilar data packets is involved. In order to measure amount of data packets sent from source node received at sink node is utilized by various parameters. Taking into consideration of traffic and congested routes improves packet delivery ratio. The proposed method is used for choosing optimal route by data aggregation and sending respective data packets to sink node is improved. Further, Kullback Leibler Sparsity Measure is used in hidden layer and sensor nodes participating in data aggregation enhances congestion control. As a consequence, likelihood for transmitting sensor nodes to reconstruct loss function involved in data aggregation in preceding cycle. In addition, Kullback Leibler Sparsity Measure is used in hidden layer of Sparse Auto Encoder with low loss function leads formation of congestion control data aggregation followed by data delivery with a maximum packet delivery ratio. As a result, the packet delivery ratio using KL-SAE is found to be better than 4% compared with KL-SAE, FSMC and 7% compared with AWFCC respectively.

5. Conclusions

This paper has proposed a traffic and congestion-control data delivery method called, Kullback Leibler Sparse Auto Encoder (KL-SAE) for wireless sensor networks. The proposed method uses machine learning and deep learning to perform data delivery. First, an Energy-efficient Q-Learning based Traffic-aware Routing by employing energy consumption and queue length as reward is designed to identify optimal route with minimum time and overhead. Further, Kullback Leibler Sparse Auto

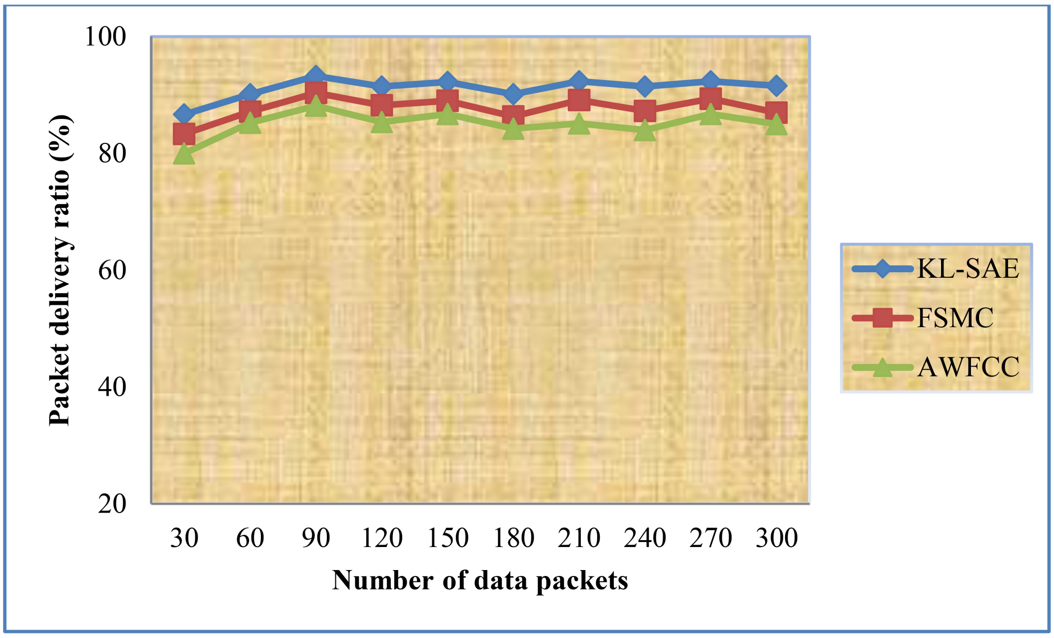

Figure 10: Graphical representation of packet delivery ratio

Encoder (KL-SAE) Congestion-control Data Delivery model was applied for data aggregation and reduce the congestion involved by means of Kullback Leibler function that with the aid of sparsity measure not only improves packet delivery ratio minimizes packet loss rate significantly. The proposed method is efficient in various parametric. Therefore, proposed method aggregates data packets by optimal route that decreases the routing time, overhead, improves packet delivery ratio, which ultimately decrease packet loss rate respectively.

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