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STEPWISE REGRESSION BASED SUPPORT VECTOR MACHINE FOR STABLE AND CONSISTENT DATA DELIVERY IN WSN

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ABSTRACT* — *Wireless Sensor Networks (WSNs) plays an important function with self-organized and structure-less wireless networks for data delivery. With different routing protocols, efficient route path is selected by using the stable links. The establishment of stable network topology ensures communication effectiveness without any disconnection or disruption, for providing reliable data transmission. But, present network protocol modifies the route path considerably due to different interferences and environmental changes. Though, it obtains minimum data stability. Therefore, Stepwise Regression based Support Vector Machine (SR-SVM) technique is introduced to improve stable and consistent data delivery in WSN. Stepwise Regression technique and Support Vector Machine are the two process involved in proposed SR-SVM technique. At first, Stepwise Regression technique is used to examine the neighbouring node and select the target node. Based on neighbouring node, energy efficient neighbouring node is detected to attain a stable data delivery with minimum energy consumption in network. With the help of detected energy node, target node is selected for efficient wireless communication. After that, consistent data delivery is attained in network through link quality measure by using Support Vector Machine (SVM). Here, the link quality of the neighbouring nodes is considered to choose the optimal route by minimizing the distance function. In addition, convex hull of the two classes is used in geometric representation of SVM. Here, the number of hop between source and sink nodes are determined. This helps to improve link quality and network consistency with reduced data packet loss. The performance of SR-SVM technique is evaluated with parameters such as throughput, energy consumption, data loss rate, and average time. The experimental result shows that SR-SVM technique achieves higher throughput and better energy consumption when compared to state-of-the-art-works.

Keywords: Wireless sensor networks, Stepwise Regression technique, Support Vector Machine, Convex Hull

1. INTRODUCTION

Wireless sensor networks attain stable and high consistent data delivery with the required performance of data communication. The improvement of consistent wireless network communication provides better communication with reduced data loss and delay during data transmission between the sensor nodes. Here, Stable and unstable links were distinguished. Therefore, the several research works has been established in WSN for stable and consistent data delivery. It is explained with the help of literature work as follows.

Competence-enhanced and Maintenance Distance Vector (MC-DV) framework was considered in [1] to develop the performance of network with feedback control. With the aid of every link, transmission power and retransmission were adjusted to attain higher delivery ratio. Kautz-based Real-time, Fault-tolerant and EneRgy-efficient WSAN (REFER) was discussed in [2] to get real-time communication. It includes multi-path based routing and energy-efficient to improve network performance. Though, the delay is increased with minimum network lifetime.

A multihop wireless routing protocol named as E-STAR was developed in [3] systems to enhance the performance of routing with high consistency and stability. It increases the packet delivery ratio and network lifetime. But, it fails to enhance the link stability. In [4], Enhance Threshold Sensitive Stable Election Protocol (ETSSEP) was considered to improve the stability of routing with increased network lifetime. Though, it considers only stability and failed to improve the reliability of network.

Unequal redundancy level (URL) data collection scheme was designed in [5] to attain reliable data communication. With the assist of network coding-based mechanism, energy consumption is balanced at both non-hotspot areas and hotspot areas. But, delay was increased. Data Routing for In-Network Aggregation (DRINA) was presented in [6] to provide reliable routing. Here, data fusion and aggregation is avoided to preserve the energy during communication. Thus, it reduces energy consumption. But, network throughput is not considered.

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Power Emission Density (PED)-based interference modeling method was designed in [7] for enabling accurate network settings. Sector-based resources allocation scheme is used to enhance the throughput rate. But, it resulted with higher energy consumption to the desired level. In [8], double level-low-energy adaptive clustering hierarchy (DL-LEACH) algorithm was discussed to determine node energy and to select cluster head for minimum energy consumption. However, the consistency of data transmission was not improved.

Local Uniform Rate Service (LURS) was implemented in [9] which are known as calculus framework to improve energy efficiency. Based on backlogged data and delay restrictions, better energy is maintained along with scheduling cycle. But, data stability is not maintained properly. In [10], Energy-efficient multi-layer MAC (ML-MAC) protocol was introduced to reduce the energy consumption with minimum collisions and retransmission. But, energy efficiency is high. The issues presented in the existing literature such as lower network throughput and energy consumption. In order to overcome such issues, Stepwise Regression based Support Vector Machine (SR-SVM) technique is introduced in WSN. The main contribution of the research work is described as follows,

- To improve stable and consistent data delivery, Stepwise Regression based Support Vector Machine (SR-SVM) technique is introduced. Initially, Stepwise Regression technique is applied to select a target node by monitoring the neighbouring node and thus it achieve stable data delivery. With the support of target node, energy consumption is minimized.
- Next, Support Vector Machine (SVM) is used in SR-SVM technique to improve the consistency of network during data delivery through link quality measure. The optimal route path is selected by measuring the link quality of the neighbouring nodes. The convex hull of two classes in geometric representation of SVM is used to improve network consistency with reduced data packet loss.

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The rest of the paper is structured as follows: In Section 2, Stepwise Regression based Support Vector Machine (SR-SVM) technique 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.

2. STEPWISE REGRESSION BASED SUPPORT VECTOR MACHINE TECHNIQUE

The Wireless Sensor Network is designed for enhancing the data delivery ratio to the one hop neighbour with efficient energy of sensor nodes. The sensor node determines target node (i.e. one hop neighbouring node) to achieve improved network stability and consistency with minimum energy consumption. Therefore, an efficient data packet delivery is obtained with minimum delay, energy consumption and less hop count for improving the sensor node communication. Therefore, Stepwise Regression based Support Vector Machine (SR-SVM) technique is proposed to attain stable and consistent data delivery.

A system model for proposed SR-SVM technique is considered to achieve stable and consistent data delivery in WSN. Let us consider, a wireless sensor network which comprises of a graph '$G = (V, E)$' where 'V' denotes a number of sensor nodes $SN_1, SN_2, \dots, SN_n$ and 'E' denotes edge i.e. links between the nodes in a sensing rectangular area '$M * N$' in a communicate range 'r'. Let 'NN_n' is the set of neighbour's node. The sensor nodes develop the necessary transmission range to execute stable and consistent data delivery in WSN. Based on the system model, the performance analysis of proposed SR-SVM technique is carried out. The architecture diagram of Stepwise Regression based Support Vector Machine technique is shown below.

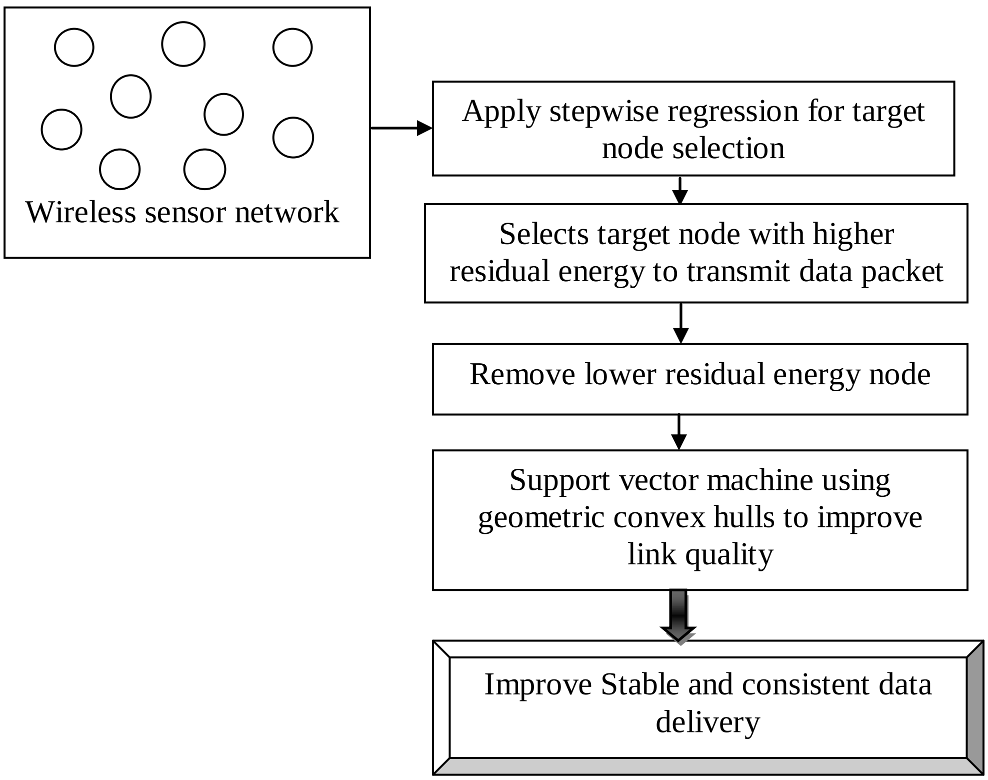

Figure 1 Architecture Diagram of Stepwise Regression based Support Vector Machine technique

Above figure 1 illustrates the architecture diagram of the Stepwise Regression based Support Vector Machine (SR-SVM) learning technique. Here, WSN consists of different numbers of sensor nodes. The SR-SVM technique includes two processes such as stepwise regression and support vector machine using geometric convex hulls. Initially, Stepwise Regression is used for selecting the target node in network to achieve improved data packet delivery in WSN. Based on the energy of each sensor node, the target node (i.e. neighbouring node) is selected. The data packets are transmitted when the residual energy is higher during selection of target node. After that, support vector machine using geometric convex hulls is introduced to improve link quality. It reduces the nearest point difficulty which directs to efficient solution for geometric representation of SVM thereby reducing the data loss and

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average time for next hop selection. As a result, proposed SR-SVM technique achieves stable and consistent data delivery in WSN.

2.1 Stepwise Regression for target node selection

An efficient target node selection is carried out through stepwise regression technique to obtain improved stability on data. In sensor network, both link stability and node stability is important to improve the consistent data delivery in WSN. Thus, it is achieved by using stepwise regression technique. Regression is a geometric measure to establish the strength of correlation between one dependent variable (i.e. nodes) and a sequence of independent variables (i.e. nodes). There are two significance processes namely variable selection and removal. Based on the energy utilization of sensor node, process is carried out. During this process, higher residual energy is selected as a target node for data packet transmission. When there is a lower residual energy, then the node is removed and it helps to avoid the path failure in network. Hence, the link stability is improved while broadcasting the data packets.

Let us consider, the number of sensor nodes '$SN_1, SN_2, \dots, SN_n$' and the transmitting and receiving energy of the node are measured. The energy of the node is measured in terms of power and time as given below.

$$Energy = P * time \qquad (1)$$

From (1), energy of node is measured with power 'P' and time in seconds. The energy of each node is measured in joules. The transmitting energy of a node is calculated as follows.

$$E_{tr} = \frac{P_T * 8 * DP_{size}}{B} \qquad (2)$$

From (2), a transmitting energy 'E_{tr}' is measured using transmission power represented as 'P_T', a size of data packet given as 'DP_{size}' and the bandwidth denoted as 'B'. Thus, it determines the amount of data packet is transmitted in a fixed amount of time. The energy consumption of receiving a data packet is calculated as following.

$$E_{Rr} = \frac{P_R * 8 * DP_{size}}{B} \qquad (3)$$

From (3), a receiving energy is specified as 'E_{Rr}' and 'P_R' denotes a receiving power. After that, the total energy of sensor node is measured using following equation.

$$E_T = E_{tr} + E_{Rr} \quad (4)$$

A total energy of a node 'E_T' is measured using (4). In order to select the target node, residual energy is necessary for improving the link stability while broadcasting the data packets and it determines the node energy. The residual energy of sensor node is estimated as,

$$RE = E_I - E_T \quad (5)$$

From (5), the residual energy 'RE' is measured using the initial energy 'E_I' and the total energy 'E_T' required for transmitting and receiving energy. Then the threshold is assigned for selecting the target node (i.e. neighbour node).

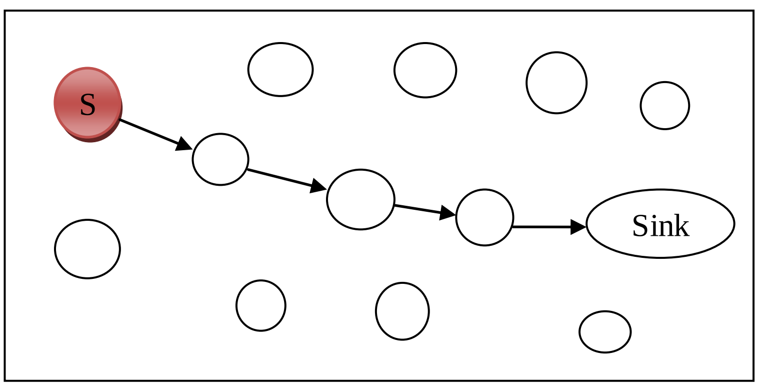

Figure 2 Target Node Selections

As shown in figure 2, the source node (S) selects neighbouring node as a target node with higher residual energy to execute data delivery. Stepwise Regression technique is used in SR-SVM technique to select a dependent sensor node as a target node and remove the independent nodes based on residual energy. As a result, a better target node in network is selected for efficient data packet transmission.

// Stepwise Regression based target node selection

Input: Sensor nodes$SN_1, SN_2, \ldots, SN_n$, Data Packet '$DP_i = DP_1, DP_2, DP_3 \ldots, DP_n$

Output: Target node selection to improve throughput and minimize energy consumption

Step 1:Begin

Step 2: **For** each sensor node in network

Step 3: Measure transmitting and receiving energy of node using (2) (3)

Step 4: Compute residual energy of sensor node using (5)

Step 5: **If** (RE ≥ T_H) then

Step 6: Select the target node for transmitting data packets to sink node

Step 7: **Else**

Step 8: Removes the node which has lower residual energy

Step 9: **End If**

Step 10: **End For**

Step 11: **End**

Algorithm 1 Stepwise Regression based target node selection

Stepwise Regression based target node selection algorithm is described in above algorithm 1. For each sensor node, transmitting and receiving energy is measured. Then, the residual energy of sensor node is calculated for selecting their one hop neighbouring node by comparing with threshold value. If residual energy of the node is higher than the threshold value, the node is selected as target node to perform data delivery. Otherwise, when there is a lesser residual energy, then the sensor node is removed. This helps to improve the throughput and reduce the energy consumption.

2.2 Geometric representation of Support vector machine learning technique

Next, Support Vector Machine (SVM) learning technique is applied to improve the network consistency by measuring the link quality. It reduces the transmission range and multiple hops between the nodes in network. When there is higher link quality, data packets are transmitted with neighbouring nodes and consistency is improved with one-hop communication. The support vector machine contains set of training samples '$\{(x_1, y_1), (x_2, y_2), \ldots (x_i, y_i)\}$' i.e.

group of sensor nodes. From the samples, 'x_i' indicates sensor nodes and 'y_i' indicates output results. The output of SVM is described as '$Y \in \{+1, -1\}$'. Based on convex set, convex hull and extreme point set, geometric representation of SVMs is performed. At first, convex set is shown in figure 3 with a set of points (i.e. sensor nodes) where any two sensor nodes SN_1 and SN_2 are connected and the line denotes a connection of two nodes lies totally within the set.

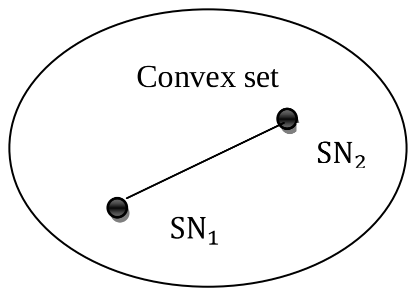

Figure 3 Convex set

Secondly, Convex Hull in figure 4 provides a set of points (i.e. nodes) in the Euclidean plane. Formally, the convex hull of the set is the smallest convex polygon that includes the number of nodes of it.

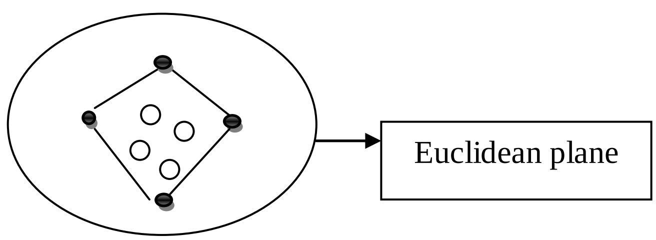

Figure 4 Convex hull

Finally, an extreme point of a convex set 'S' is a point which does not lie in any open line section combining two points. As the number of node increases, SVM learning technique uses convex hulls to control the nodes and to avoid limited transmission range problems. The geometric SVMs are applied using geometric convex hulls to improve the link quality. The convex hull of a finite set 'S' is defined as a set of combination with all convex and each point 'x_i' (i.e. nodes) is assigned as a weight μ_i to determine average weighted points. A SVM is a discriminative classifier which is described by a separating hyperplane. It bisects the straight vector joining the convex hulls of the positive and negative polarity points. The geometric

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representation of the SVM is described in a separable case. Here, additional nodes do not disturb the final solution unless they redefine the margin of the hyperplane. The margin which is above and below the hyperplane is defined as follows,

$$H^{+} \rightarrow \vec{w}.\vec{x} - \vec{b} = +1 \qquad (6)$$

$$H^{-} \rightarrow \vec{w}.\vec{x} - \vec{b} = -1 \qquad (7)$$

From (6), (7), H^{+} and H^{-} defines a margins of two classes, $\vec{w}$ denotes a weight vector, $\vec{x}$ denotes a set of points (i.e. nodes) and $\vec{b}$ denotes a bias. Therefore, an optimal hyperplane is described as the set of points and given as below.

$$\vec{w}.\vec{x} - \vec{b} = 0 \qquad (8)$$

Therefore, convex hull of the two classes are defined as,

$$H^{+} = \left\{ \sum_{y_i=+1} \mu_i x_i \,\middle|\, \sum_{y_i=+1} \mu_i = 1 \;\; , \mu_i \geq 0 \right\} \qquad (9)$$

$$H^{-} = \left\{ \sum_{y_i=-1} \mu_i x_i \,\middle|\, \sum_{y_i=-1} \mu_i = 1 \;\; , \mu_i \geq 0 \right\} \qquad (10)$$

From (9) and (10), an average weight of each point is denoted as 'μ_i' in the convex hull. With the aid of geometric representation of SVMs, optimal node is selected and determining the two closet nodes as the optimization functions. As a result, an efficient route path is identified for link quality measurement and attains consistent network communication. Next, the data packet is transmitted to next hop node by finding the closest node. Hop node is defined as intermediate nodes between sources and sink node and it reduces the hop distance with minimum time. Thus, the two closest nodes as the optimization functions are defined as follows.

$$\min_{\mu_i \geq 0} \left\| \sum_{y_i=+1} \mu_i x_i - \sum_{y_i=-1} \mu_i x_i \right\|^2 \qquad (11)$$

$$\text{Such that,} \quad \sum_{y_i=+1} \mu_i = 1, \sum_{y_i=-1} \mu_i = 1, w_i \geq 0$$

The decision boundary is considered as f(x) = $\vec{w}.\vec{x} - \vec{b} = 0$ to be the perpendicular bisector of the line segment combining the two closest nodes in the network,

$$w = \frac{1}{2}\left(\sum_{y_i=+1} \mu_i x_i - \sum_{y_i=-1} \mu_i x_i\right) \quad (12)$$

$$q = \frac{1}{2}\left(\sum_{y_i=+1} \mu_i x_i + \sum_{y_i=-1} \mu_i x_i\right) \quad (13)$$

From (12) and (13), w lies along the line section and q denotes a midpoint of the line section. By rescaling the objective function, the output class labels '$y_i = \pm 1$' is attained. Therefore it is formularized as,

$$\min_\mu \|w\|^2 = \frac{1}{4}\sum_{ij} \mu_i\, y_i x_i \quad (14)$$

The decision function by using the convex hull is attained as follows

$$f(x) = \sum_{i,\epsilon x} \mu_i y_i\ x_i + \mathrm{b} \quad (15)$$

The sign of the decision function f (x) find whether data point 'x' lies on the positive or negative side of boundary and f (x) = 0 denotes a border line. Therefore, the node located in boundary and other problems are avoided by the convex hull of the geometric representation of the SVM. The algorithmic explanation of the SVM learning technique is described as follows.

Input : Data points i.e. Sensor nodes$SN_1, SN_2, \ldots, SN_n$, weight μ_i, output function y_i

Output: Improve the network Consistency with minimum data loss and average hop count

Step 1: Begin

Step 2: For all sensor node SN_i in network

Step 3: Convex hull of two classes is defined using (9) (10)

Step 4: Find two closest points by minimizing the distance formula using (11)

Step 5: Measure the objective function using (14)

Step 6: Measure the decision function using convex hull (15) for avoiding limited transmission range problem

Step 7: Sensor Nodes closest distance are selected to improve link quality for transmitting data packet

Step 8: End for

Step 9: End

Algorithm 2 Support Vector Machine learning algorithm

From above algorithm, the consistence of network is improved for reducing the data packet loss and time for next hop selection. At first, convex hull reduces limited transmission range problem in separable case and minimizing the distance function. Based on the node distance, the link quality is improved. Therefore, the data packet is transmitted along the route and reduces the data packet loss. As a result, the SR-SVM Technique efficiently improves the stable and consistent data delivery in WSN.

3. SIMULATION SETTINGS

The proposed Stepwise Regression based Support Vector Machine (SR-SVM) technique is simulated using NS-2 simulator with the network range of 1200*1200 m size. Destination Sequence Based Distance Vector (DSDV) is used as routing protocol to conduct the experimental work. It consists of different 100 nodes and 90 data packets with varies sizes ranges between 100 to 1000 KB. The mobility of the sensor node is about 10 m/s with simulation rate of 45 milliseconds for data transmission.

4. RESULTS AND DISCUSSION

Result analysis of Stepwise Regression based Support Vector Machine (SR-SVM) technique is discussed and compared with two existing methods. The compared existing methods are namely Competence-enhanced and Maintenance Distance Vector (MC-DV) [1] and A Kautz-based REal-time, Fault-tolerant and EneRgy-efficient WSAN (REFER) [2]. The performance analysis is conducted on the factors such as throughput, energy consumption, data loss rate and average time for stable and consistent wireless network communication. The performance of SR-SVM technique is described with the help of tables and graphs.

4.1 Performance analysis of Throughput

The ratio of number of data packets received at the sink node according to the total data packets transmitted is defined as throughput. It is measured in kilo bits per second (kbps).

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

From (16), 'DP_{Sink}' data packets are sink node and 'DP_S' data packet send.

Table 1 Tabulation for Throughput

Data Packet size (KB)	Throughput (Kbps)		
	SR-SVM	MC-DV	REFER
100	65	35	60
200	137	72	120
300	190	120	170
400	270	180	244
500	330	250	310
600	335	260	315
700	399	295	370
800	497	395	470
900	555	470	540
1000	610	520	590

Table 1 clearly describes the throughput with respect to different packet sizes used in simulation analysis. The size of the data packet is varied from 100KB to 1000KB. If the data packet size is increased then the throughput gets increased. But the proposed SR-SVM technique shows better throughput than existing MC-DV [1] and REFER [2].

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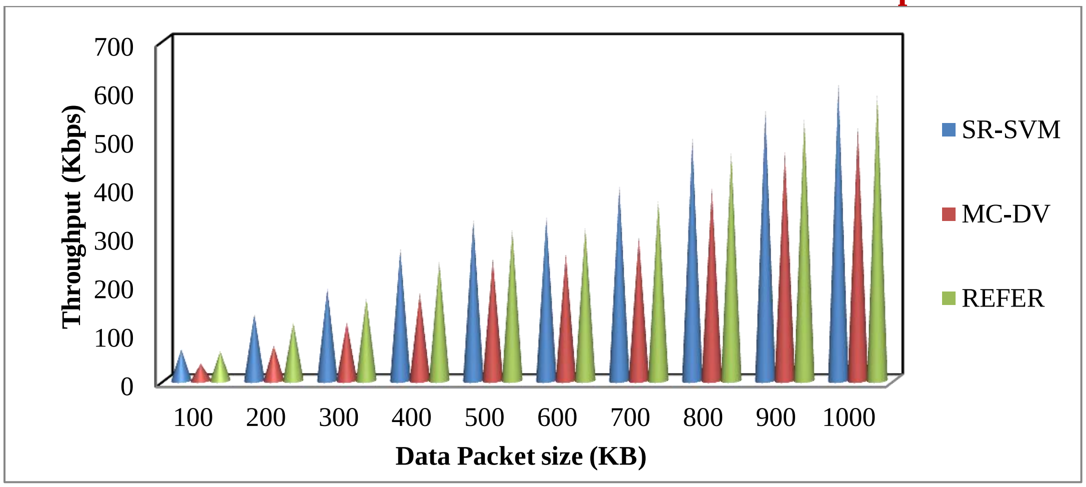

Figure 5 Performance measure of throughput

Figure 5 illustrates the performance analysis of throughput rate with respect to different data packet size. Above figure shows the comparison result of proposed SR-SVM technique with existing MC-DV [1] and REFER [2]. With the application of stepwise regression technique, target node is selected and remaining nodes are removed based on their residual energy. When there is a higher residual energy, the route path is generated between sources and sink node. Thus, it helps to improve the data delivery ratio and resulted with higher throughput. Therefore, SR-SVM Technique considerably enhance the throughput by 44% and 8% compared to existing MC-DV [1] and REFER [2] respectively.

4.2 Performance analysis of energy consumption

Energy consumption is defined as an amount of energy consumed by a single sensor node 'E_{SN}' with respect to the total number of sensor nodes 'N' in WSN. Energy consumption is measured in terms of joules (J).

$$EC = E_{SN} * N \quad (17)$$

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Table 2 Tabulation for energy consumption

Sensor nodes (N)	Energy consumption (J)		
	SR-SVM	MC-DV	REFER
10	35.2	50.3	42.7
20	38.7	54.9	46.5
30	42.9	59.2	50.4
40	48.2	63.9	55.7
50	50.6	65.6	57.6
60	53.5	68.3	60.3
70	55.9	71.8	63.8
80	58.7	73.7	65.2
90	63.5	78.6	70.4
100	66.1	82.4	73.9

Above table 2 shows the simulation value of energy consumption with respect to different number of sensor nodes. The sensor nodes are varied from 10 to 100 nodes. As shown in above table, the proposed SR-SVM technique reduces energy consumption when compared with existing MC-DV [1] and REFER [2] methods.

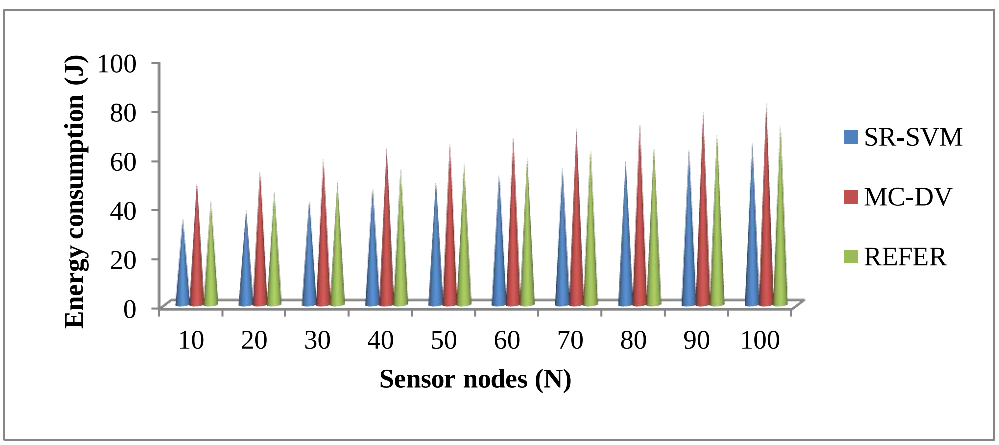

Figure 6 Performance measure of energy consumption

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The performance analysis of energy consumption with respect to varies sensor nodes is illustrated in above figure 6. From the figure, proposed SR-SVM technique significantly outperforms than the existing methods. Here, stepwise regression technique is used to reduce the energy consumption of sensor node during the transmission. In order to obtain minimum energy consumption, target node is selected based on the residual energy of nodes. Additionally, it constructs the route path with minimum energy utilization for efficient data packet delivery. As a result, the energy consumption is reduced by 24% and 13% compared to existing MC-DV [1] and REFER [2] respectively.

4.3 Performance analysis of data loss rate

The difference between the size of data packet received at sink node '$DP_{sink}(size)$' and size of data packet send '$DP_S(size)$' in WSN is defined as data loss rate. It is measured in kilo bytes (KB).

$$Data\ Loss\ Rate = DP_{sink}(size) - DP_S(size) \qquad (18)$$

Table 3 Tabulation for data loss rate

Data Packet size (KB)	Data loss Rate (KB)		
	SR-SVM	MC-DV	REFER
100	27	38	32
200	32	43	37
300	34	45	39
400	32	43	37
500	37	48	42
600	40	51	45
700	37	49	42
800	42	53	47
900	44	55	49
1000	45	57	50

Table 3 describes the analysis of data loss rate based on size of data packet. The data packet sizes get varied from 100 to 1000 KB. When the size of data packet is increased, data loss rate is also increased. Hence, the proposed SR-SVM technique reduces the data loss rate when compared with existing MC-DV [1] and REFER [2] methods.

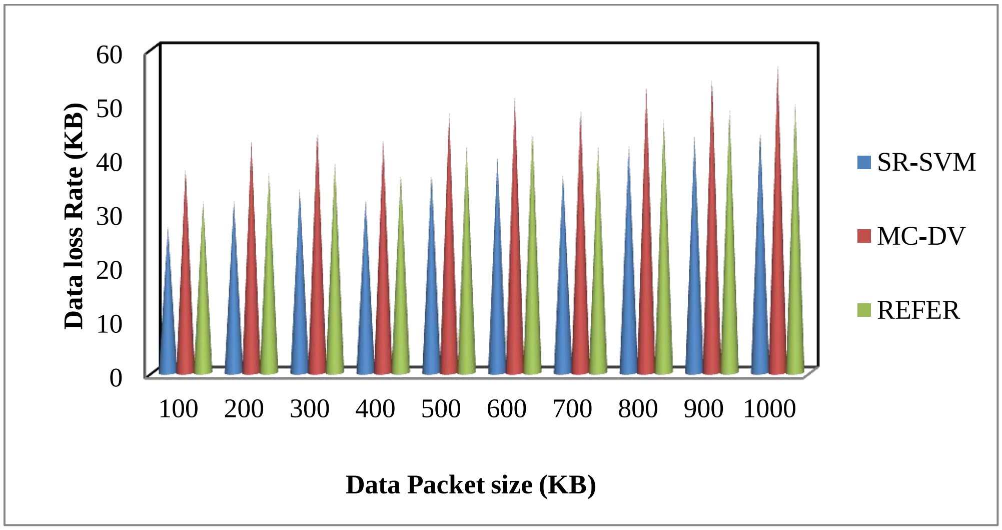

Figure 7 Performance measure of data loss rate

The performance analysis of data loss rate with respect to varies data packet size is illustrated in above figure 7.The data loss rate is determined based on optimal route path. By applying the geometric representation of the SVM learning technique, optimal route path is attained. In addition, link quality is improved based on the distance between source nodes to sink node and avoids the limited transmission range problem. Hence, the data packets are transmitted along that route path with minimum hop. This helps to improve the consistent data delivery and reduce the data loss rate. Therefore, the data loss rate is minimized by 24% and 12% when compared to existing MC-DV [1] and REFER [2] methods respectively.

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4.4 Performance analysis of average time

The average time is defined as the measure of time taken for selecting next hop node between source nodes to sink node according to the total number of sensor nodes in WSN. It is measured in terms of milliseconds (ms).

$$Average\ Time = time\ (selects\ the\ next\ hop) \tag{19}$$

Table 4 Tabulation for average time

Sensor nodes (N)	Average time (ms)		
	SR-SVM	MC-DV	REFER
10	12.8	22.4	16.8
20	16.5	25.7	20.4
30	20.2	29.3	23.7
40	23.5	33.5	27.9
50	27.6	37.4	31.6
60	31.2	41.9	35.9
70	35.9	45.8	40.4
80	39.5	50.3	44.5
90	41.2	52.2	46.9
100	43.1	53.4	48.2

As shown in table 4, the measure of average time value is tabulated based on the different number of sensor nodes. The average time for determining the next hop is reduced in proposed SR-SVM technique when compared with existing MC-DV [1] and REFER [2] methods.

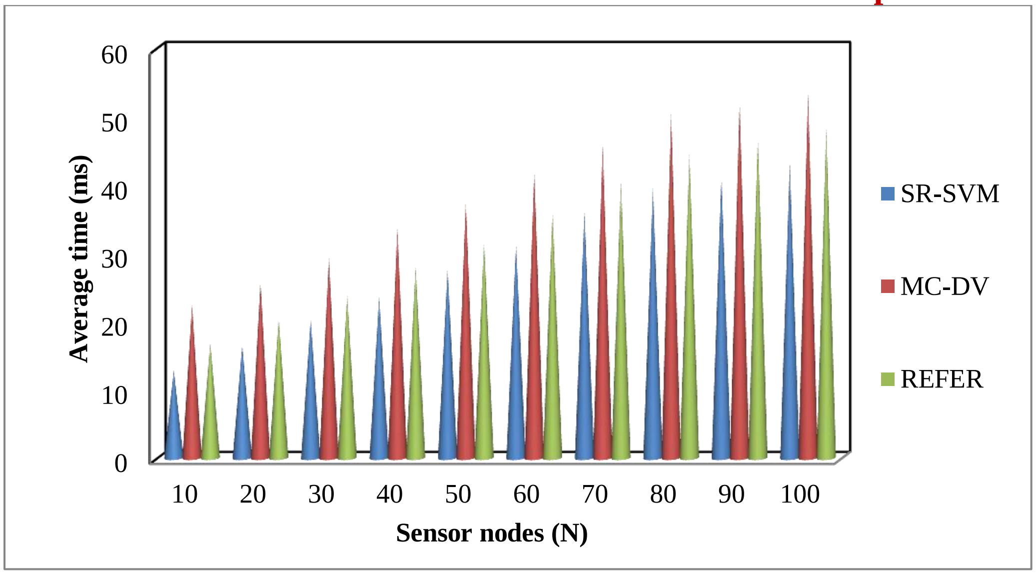

Figure 8 Performance measure of average time

Figure 8 describes analysis of average time with respect to number of sensor node in the range of 10 to 100 nodes. By applying the support vector machine learning technique, number of hops between source and sink node is reduced. The next hop node is selected with higher residual energy for every sensor node. Thus, it generates the link between nodes to achieve successful data delivery and improves the network consistency. As a result, the average time for selecting the next hop node is reduced by 27% and 14% when compared to existing MC-DV [1] and REFER [2] methods.

5. RELATED WORK

Zone-based Energy Efficient routing protocol (ZEEP) was described in [11] to select the best optimal nodes for communication. Then, a genetic algorithm is used to improve network lifetime with minimum energy consumption. Though, it does not consider data stability. Genetic Algorithm based approach in multi-sink WSN was developed in [12] to determine the difficulty of load balance. With the assist of Genetic algorithm, the coverage area is increased by controlling the communication. However, the network throughput was reduced.

Another Genetic algorithm was introduced in [13] to provide an energy-efficient based multipath routing. A-star algorithm was performed to establish higher route stability and reduced multipath traffic. However, network throughput was not improved. Mobile sink based Energy efficient adaptive threshold clustering hierarchy algorithm was presented in [14] to solve network lifetime and load balancing. Predictive Energy Consumption Efficiency (PECE) was designed in [15] to improve network lifetime. With the use of bee colony optimization (BCO), stable data transfer is obtained. But, throughput and energy consumption was not considered.

6. SUMMARY

Finally, an efficient Stepwise Regression based Support Vector Machine (SR-SVM) technique is introduced for achieving stable and consistent network communication. In the beginning, stepwise regression technique is applied to select the target node for transmitting the data packet and it is selected based on node energy. When the node has higher residual energy, throughput is increased with minimum energy consumption. After that, support vector machine learning technique is used to improve network consistency. Here, link quality is measured by geometric representation of SVM. With the help of convex hull, next hop node is determined. This helps to reduce the data loss rate. Finally, the decision functions of convex hull of SVM avoid the limited transmission problem and improve the network consistency.

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