

Triangular Fuzzified Support Vector Regression Based Multivariate Rocchio Robust Boost Classification for Traffic and Congestion Aware Data Delivery in WSN

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Abstract

Wireless sensor network (WSN) is a huge set of sensor nodes distributed geographically with limited power supply. These nodes are used to sense environmental changes, gather information and send the collected data to a remote destination for data analysis and decision making. During continuous data transmission, the network traffic causes congestion. Congestion in WSN is a major cause for packet loss and it degrades the network performance. In order to improve the congestion-aware routing, a novel technique called as the Triangular Fuzzified Support Vector Regression Based Multivariate Rocchio Robust Boost Classification (TFSVR-MRRBC) technique is introduced. The proposed TFSVR-MRRBC consists of two processes such as route path identification and congestion aware data delivery. Initially, route paths are constructed by estimating node residual energy. After that, Support Vector Regression is applied to analyze the energy using the fuzzy Triangular membership function. Thus, energy-efficient nodes construct the multiple paths between sources and sink node through control message distributions namely route request with route reply is identified. Then the Multivariate Rocchio adaptive robust boost technique is applied for congestion aware data delivery based on the buffer space and bandwidth capacity. The route path with low buffer space and higher bandwidth capacity is selected as the best route among the multiple paths. Finally, Delay and packet loss is reduced by achieving congestion-aware data delivery. The simulation is achieved by various performance factors namely, energy consumption, packet delivery ratio, packet loss rate, and end-to-end delay with versus to amount of data packets and sensor nodes. Experimental results of proposed TFSVR-MRRBC technique improves data packet delivery and energy consumption is minimized, packet loss rate, delay than the conventional routing techniques.

Key-words: WSN, Route Path Identification, Data Delivery, Support Vector Regression, Fuzzy Triangular Membership Function, Multivariate Rocchio Adaptive Robust Boost, Congestion, and Traffic-aware Routing.

1. Introduction

Wireless Sensor Network (WSN) has various low-power microsensor devices utilized in geographical area for remote sensing, surveillance, control, and monitoring utilization. It provide different services namely, user-friendly interface, small range, and less operation rate that helps to various smart wireless sensor networks (WSNs) applications. In large-scale utilization of WSNs, namely environment monitoring scenarios, hundreds of sensor nodes is positioned through huge coverage-area. The number of nodes is activated and numerous data is transmitted which cause the cause the traffic, directing to congested areas. The performance of WSN has harmful impact and also reduces throughput, enhances packet retransmission, and wastage of energy. The conventional routing has been developed for congestion aware data delivery in WSN

An Energy and Congestion Aware Routing (ECAR) algorithm was developed in [1] for forwarding data packets by smaller congestion and energy-saving path. But the designed algorithm failed to reduce average energy consumption of nodes and network lifetime is improved. Jellyfish Dynamic Routing Protocol (JDRP) is proposed in [2] for congestion avoidance. The designed protocol increases the performance of energy consumption with lesser delivery of packet but delivery rate is not improved.

A Congestion-aware Clustering and Routing (CCR) protocol is developed in [3] for improving Quality of Service (QoS) requirements and network period. But designed protocol failed to decrease the energy used for efficient data delivery. An Optimized Fuzzy Logic-based Congestion Control method was introduced in [4] for path determination architecture to avoid congested routes and extend the network. But the architecture failed to consider the heterogeneous data traffic implementation.

An exponential-reaching-law-based Discrete-time Sliding Mode Congestion controller (DSMC) was implemented in [5]. The method reduces the delay as well as packet loss rate, but the machine learning technique was not implemented to attain high delivery. A fuzzy-based Cross-layer mechanism using Oppositional Artificial Bee Colony (FCOABC) protocol is designed in [6] for enhancing network duration with energy efficiency. But designed protocol failed to estimate the traffic on layers using the larger density of nodes.

A multi objective clustering approach was developed in [7] to optimize the energy consumption, network life span, throughput, and delay. But performance of packet loss rate was not reduced. Traffic and Energy Aware Routing (TEAR) method is developed in [8] for achieving optimal resource utilization the node's traffic with initial energy and residual energy are considered. However, TEAR technique failed to increase the data packet delivery ratio.

An MK/HyperK/1/M queuing method was introduced in [9] for multi-sensor nodes with heterogeneous traffic. Though the method increases the throughput, the performance of delay was not reduced. A priority-based congestion-avoidance routing protocol is designed in [10] for improving throughput and reducing delay. The designed protocol reduced the traffic load but mobility of sensor nodes was unsuccessful.

1.1. Major Contributions

The most important contributions of the proposed TFSVR-MRRBC technique are summarized as given below,

- To improve the traffic-aware routing in WSN, a novel TFSVR-MRRBC technique is introduced to improve data delivery with lesser delay and packet loss rate.
- A Triangular fuzzified support vector regression is applied in the TFSVR-MRRBC technique energy-efficient nodes are obtained. The support vector regression uses the Triangular fuzzy membership function to analyze the sensor nodes of residual energy. With selected energy-efficient nodes, multiple route paths are established to improve the data delivery rate.
- To minimize the delay and packet loss rate, the TFSVR-MRRBC technique uses a Multivariate Rocchio adaptive robust boost technique for congestion-aware data delivery. The route path having with a low buffer space and higher bandwidth capacity is selected as the best route among the multiple paths using the adaptive robust boost technique. This helps to avoid congestion due to the network traffic.
- Finally, simulation analysis is conducted with the different performance metrics to validate the TFSVR-MRRBC technique against the existing methods. The results and discussion provide better performance than the conventional methods.

1.2. Organization of Paper

This article is systematized in five different sections. In section 2, related work in the areas of energy-efficient traffic-aware routing is discussed. In section 3, proposed TFSVR-MRRBC technique was described in detail. In section 4, simulation of the proposed work is presented. In section 5, comparative analysis of different metrics is presented. Finally, section 6 describes the conclusion of this article.

2. Related Works

A Minimum Weiner Spanning Tree (MWST) model was developed in [11] for an efficient data transmission based on the number of intermediate hops. But the model failed for evaluating performance of energy available to data transmission. Field-Based Routing (FBR) method was introduced in [12] to improve network period and packet reception ratio with a minimum energy dissipation rate. But performance of delay was not reduced.

Reliable Cluster-based Energy-aware Routing (RCER) protocol was designed in [13] for heterogeneous WSN. The designed protocol extends the network's lifetime and decreases routing cost, but the performance of loss rate remained unsolved. A congestion-aware routing protocol (CoAR) was developed in [14] to lessen the congestion of the network. The protocol minimizes the delay and data loss but the performance of packet delivery rate was not analyzed.

A Differentiated Rate Control Data Collection (DRCDC) method was introduced in [15] to decrease the network congestion to minimize packet loss and delay. However, resource-efficient route path was not selected for reliable data delivery. A Congestion-Adaptive Data Collection (CADC) method was introduced in [16] to effectively resolve the congestion. Though the method increases the delivery ratio, the performance of packet loss and delay was not analyzed.

A dynamic Multi-hop Energy Efficient Routing Protocol (DMEERP) was proposed in [17] for improving packet delivery ratio and reduce energy consumption with lesser delay. But the congestion-aware routing was not performed. The energy-aware cluster-based routing protocol (ECRP) was proposed in [18] to improve energy efficiency, and packet delivery ratio. But protocol failed to handle the node mobility to analyze the performance of ECRP.

A Software-Defined Network-based resource-aware QoS method was developed in [19] for avoiding congestion and managing the network resources. However, this technique minimizes delay and improves throughput, packet loss rate is not reduced. An energy-efficient and reliable routing algorithm is proposed in [20] for minimizing packet loss rate and increased the reliability of data transmission. But the algorithm failed to consider the traffic-aware routing to reduce the packet loss and delay.

3. Proposal Methodology

A WSN is a collection of wireless sensor devices used to sense, compute and transfer the sensed data to the remote sensor nodes (i.e. sink). The WSN is suffered from numerous issues namely network

topology with congestion problems that affects usage of network bandwidth. Congestion occurs when the need of resources increases accessible capacity of system, which increases delay with packet loss. In WSN, congestion is comparatively equal to traffic load balancing. The feasible outcome of avoiding congestion and excessive traffic distribution is a hot spot problem. Therefore, larger feasible scheme of network is needed to improve the data delivery and minimize the delay. In this article, traffic-aware routing technique called TFSVR-MRRBC is introduced for routing packets over crowded areas with finding energy-efficient and under-loaded nodes. The proposed TFSVR-MRRBC technique is used to construct two independent processes namely energy-efficient path identification and congestion aware data delivery, respectively

Figure 1 - Architecture of the Proposed TFSVR-MRRBC Technique

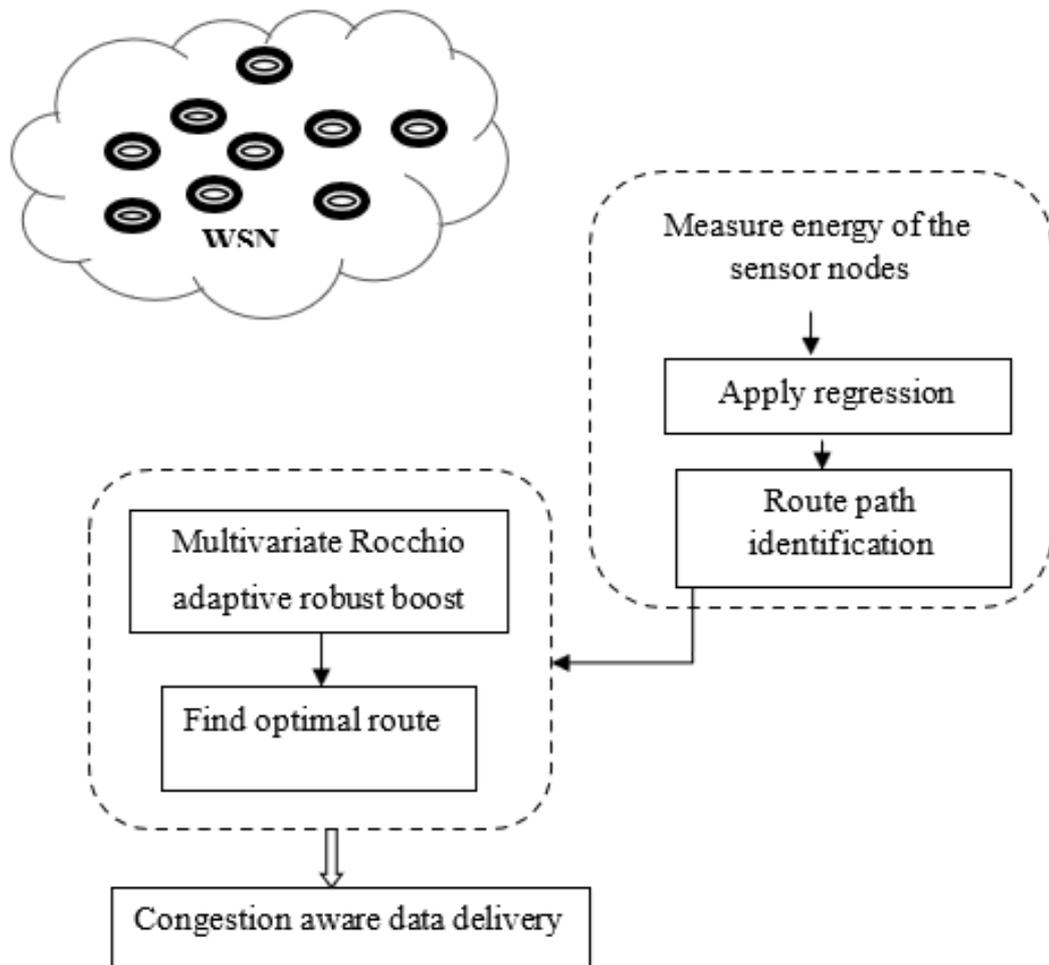


Figure 1 shows the architecture of proposed TFSVR-MRRBC technique for performing route path detection and data delivery in WSN. The proposed technique initially measures the energy for

each distributed sensor node. During request and reply messages, the route path among source and destination is established. As a result, the route with minimum distance is selected for data delivery. In the data transmission, the traffic-aware routing is performed to minimize the network congestion for reducing the delay as well as packet drop.

3.1. Network Model

A Network model of proposed TFSVR-MRRBC technique is developed. The number of sensor nodes $S_i = N_{S_1}, N_{S_2}, N_{S_3} \dots N_{S_n}$ where $0 < i < 1$ are deployed in a squared area ' $n * n$ ' within the transmission range ' t_r '. The sensor node is positioned arbitrarily and independently collects the information. The collected details or data packets ' $p_j = p_1, p_2, \dots, p_m$ where $0 < j < 1$ which is sent to sink node ' S_n ' during the energy-efficient neighboring nodes ' Nn_1, Nn_2, \dots, Nn_n to enhance the network lifetime in WSN and select route paths to avoid congestion.

3.2. Triangular Fuzzified Support Vector Regression-based Route Path Identification

The proposed TFSVR-MRRBC technique starts to perform the route path identification between the sensor nodes using the Triangular fuzzified support vector regression technique. The Triangular fuzzified support vector regression is a machine learning method is used to find relationships among dependent variable (i.e. 'outcome variable') and independent variables ('features'). Here, the regression function analyzes the 'features' of the sensor node i.e. energy.

For every sensor node in network $N_{S_1} \in WSN$, energy levels are calculated. At first, every sensor nodes have same energy level. The energy level of nodes gets degraded during the sensing process. In general, energy is formulated as given below,

$$E_{Ns} = pr * time \quad (1)$$

In equation (1), E_{Ns} indicates energy level of sensor nodes, pr indicates power, and $time$ stands for time in seconds (Sec). The sensor node is measured in joule (J). The energy level of sensor is degraded during sensing process in WSN. Therefore, the residual energy of node is measured as follows,

$$RE_{Ns} = Total_{E_{Ns}} - Cons_{E_{Ns}} \quad (2)$$

Where, RE_{Ns} symbolizes residual energy of sensor node, $Total_{E_{Ns}}$ denotes total energy of sensor nodes, $Cons_{E_{Ns}}$ symbolizes the consumed energy.

The support vector regression recognizes estimated energy level of node and finds energy-efficient nodes with the help of separating hyperplane (φ_h).

$$\varphi_h \rightarrow \alpha \cdot (x) + \delta = 0 \quad (3)$$

From (3), α indicates a normal weight vector to the hyperplane, (x) denotes sensor nodes, δ indicates a bias. The hyperplane analyzes the estimated energy level using the triangular fuzzy membership function.

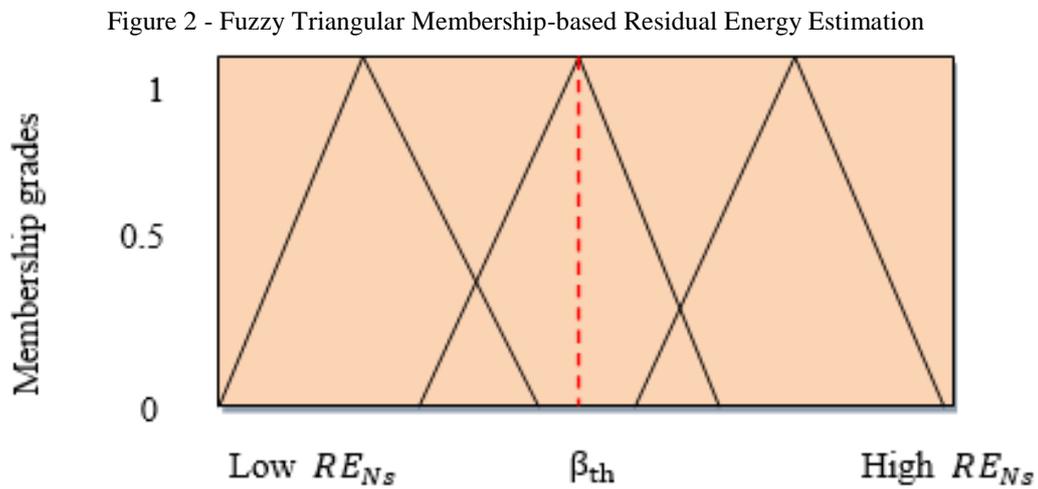


Figure 2 demonstrates the triangular fuzzy membership function based residual energy estimation. The hyperplane analyzes the residual energy of sensor node employing triangular fuzzy membership. A fuzzy membership system also uses a rule for connecting the inputs and the outputs. The rules are formulated using *if* (condition) and *then* (conclusion). The condition part verifies the estimation of sensor node by means of threshold (β_{th}) and conclusion part offers the outputs.

If the estimated sensor node of residual energy is greater than threshold (β_{th}), then hyperplane classified the sensor node as the energy-efficient node. If the estimated residual energy of sensor node is lesser than threshold (β_{th}), sensor node has low energy. The hyperplane classifies the sensor node either above or below using two marginal planes.

$$\mu_1 = \alpha \cdot (x) + \delta > 0 \quad (4)$$

$$\mu_2 = \alpha \cdot (x) + \delta < 0 \quad (5)$$

From (4) (5), μ_1 , μ_2 indicates two marginal hyperplanes i.e. above and below hyperplane. Sensor nodes of higher residual energy than threshold are classified above the hyperplane. Otherwise,

the sensor nodes are classified below the hyperplane. The energy-efficient node identification processes are shown in figure 5.

Figure 3 - Triangular Fuzzified Support Vector Regression

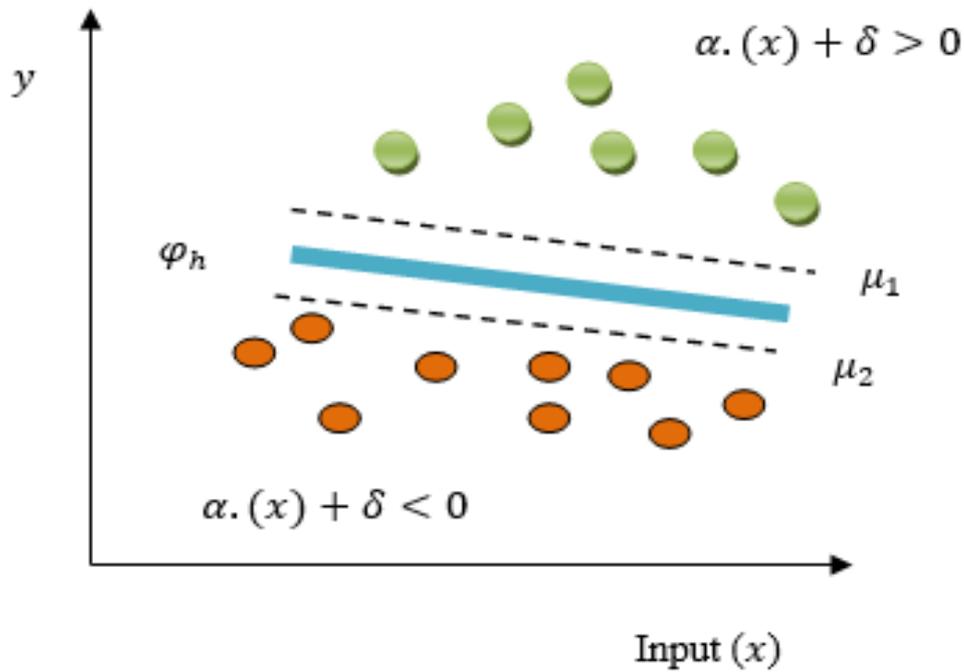


Fig 3 displays support vector regression for sensor nodes classification in energy efficient or not based on either side of the hyperplane (φ_h). After the classification, the node that has higher energy is selected for route path construction.

The multiple route paths between source and sink node are established through the two control messages namely, route request Req_R and route reply Rep_R . The requested message is distributed by source node to destination node by intermediate nodes.

$$SN \xrightarrow{Req_R} \sum_{i=1}^c (In_i) \xrightarrow{Req_R} Sn \quad (6)$$

Where SN shows source node and a route request packet Req_R is send to sink 'Sn' via the intermediate nodes (In_i). The destination replies to source node when request message is received.

$$SN \xleftarrow{Rep_R} \sum_{i=1}^c (In_i) \xleftarrow{Rep_R} Sn \quad (7)$$

From (7), ' Rep_R ' denotes a reply from sink (Sn) to source (SN) via intermediate nodes (In_i). Depend on these two control message transmissions, from source to destination the multiple routes are established as shown in figure 4.

Figure 4 - Route Paths Discovery

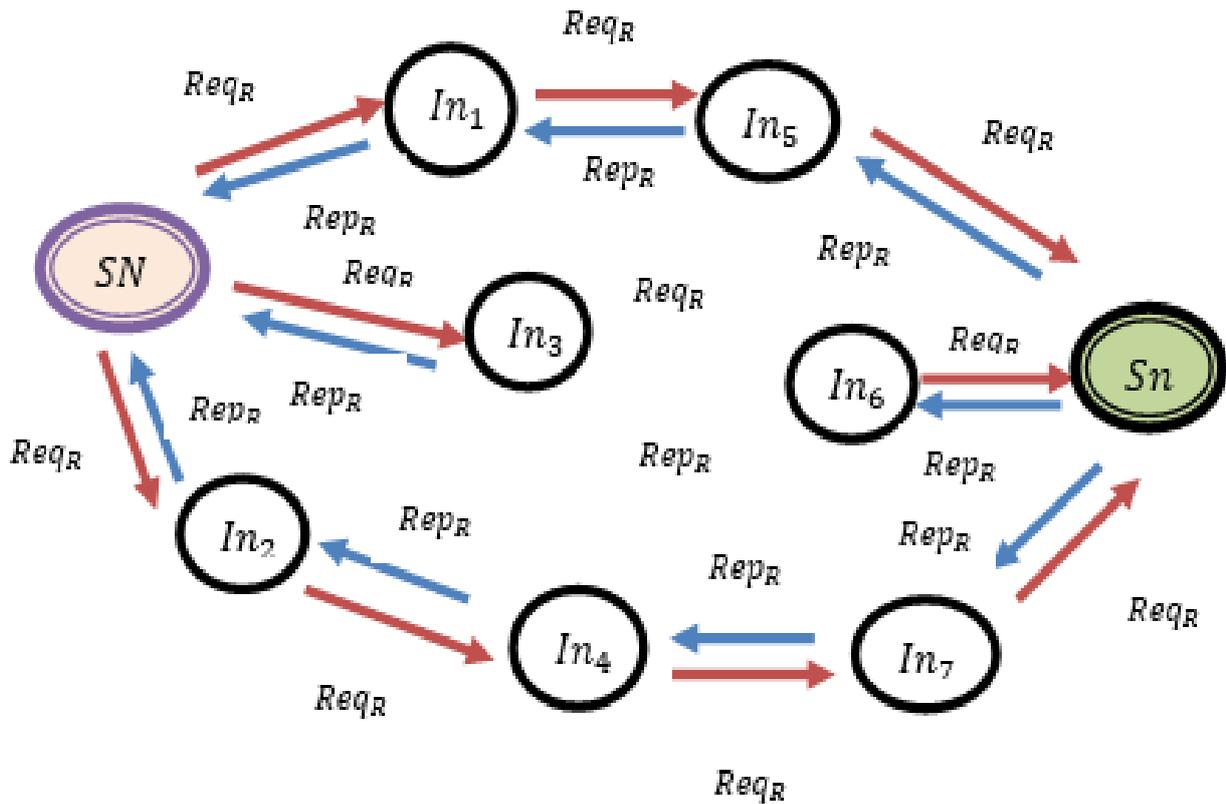


Figure 4 demonstrates the multiple paths among source and destination. Route paths from above directed graphical are listed in table 1.

Table 1 - Route Paths

Route	Route paths	Hops
r_1	$SN \rightarrow In_1 \rightarrow In_5 \rightarrow Sn$	2
r_2	$SN \rightarrow In_3 \rightarrow In_6 \rightarrow Sn$	2
r_3	$SN \rightarrow In_2 \rightarrow In_4 \rightarrow In_7 \rightarrow Sn$	3

Table 1 demonstrates the multiple route paths from source to sink node. There are three route paths r_1, r_2, r_3 , shown in table 1. The third column indicates the number of hops between the source and sink. In this way, a route path from source to destination via energy-efficient nodes is identified to improve the network lifetime.

// Algorithm 1: Triangular fuzzified support vector regression	
Input:	number of sensor nodes $S_i = N_{S_1}, N_{S_2}, N_{S_3} \dots N_{S_n}$,
Output:	Route path discovery
Begin	
1.	For each SN_i
2.	Measure RE_{NS}
3.	Analyze the RE_{NS} with threshold
4.	If ($RE_{NS} > \beta_{th}$) then
5.	SN_i is said to be energy-efficient node
6.	else
7.	SN_i is said to be low energy node
8.	End if
9.	End for
10.	Construct route paths between the source and destination
11.	SN sends Req_R to sink i.e. $SN \xrightarrow{Req_R} \sum_{i=1}^c (In_i) \xrightarrow{Req_R} Sn$
12.	Sn sends Rep_R to source i.e. $SN \xleftarrow{Rep_R} \sum_{i=1}^c (In_i) \xleftarrow{Rep_R} Sn$
13.	Create multiple routes r_1, r_2, r_3
end	

In Algorithm 1, route path discovery routing using Triangular fuzzified support vector regression is described. In WSN, residual energy levels are calculated. By employing triangular membership function, energy levels of sensor node with threshold value are estimated by regression function. The energy-efficient nodes are chosen based on analysis. After selecting energy-efficient nodes, multiple route paths are created between the sources and sink node. The multiple route paths are identified by distributing the two control messages such as route request and reply from the source to the destination and vice versa. As a result, the route paths between the nodes are identified for data delivery.

3.3. Multivariate Rocchio adaptive robust boost Congestion aware data delivery

In WSN, the major challenge is used for avoiding traffic congestion without accepting energy of sensor nodes. Since network congestion directs to packet loss, drastic reduction of throughput, and energy waste. To solve this problem, the proposed TFSVR-MRRBC technique uses the adaptive robust boost technique for traffic-aware data delivery with lesser packet loss and delay.

The robust boost technique is a machine learning method that acts as an ensemble method. The ensemble refers to the group of weak learners are combined and provides better performance than the simple alone. Weak learner is a learning algorithm which is able to produce results with probability of error. Alternatively, an ensemble method is a strong learner that is capable of providing better performance with minimum probability. The ensembles techniques are used by weak learners and combine them to provide a single strong output.

Figure 5 - Construction of Boosting Technique

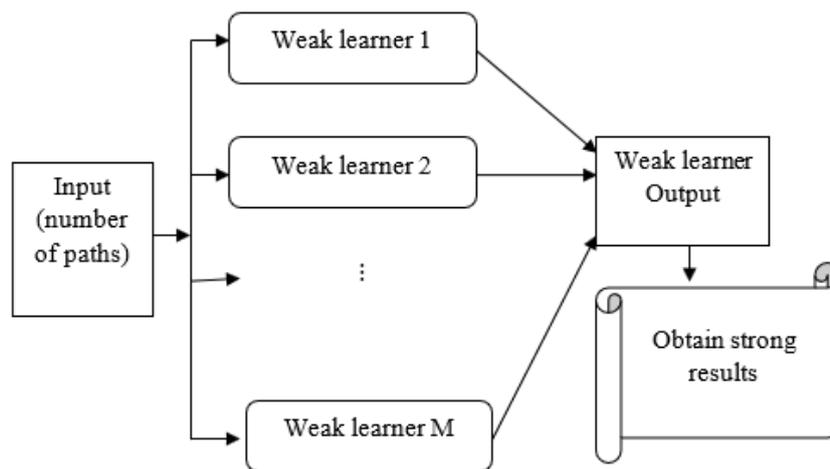


Figure 5 given above portrays the construction of the adaptive robust boosting algorithm. The input is given as training samples i.e. number of the paths. With the training samples, the weak learners are applied to identify the under-loaded nodes in the paths for congestion-aware data delivery from source to sink node. The ensemble technique constructs the numerous weak learners as a Multivariate Rocchio classifier for identifying the under loaded nodes based on two functions namely sufficient buffer space and adjusting the bandwidth over the shortest discovered route that improves the data delivery. Thus, the classifier is called as Multivariate Rocchio classifier.

For each node in the path, the under-loaded nodes are identified based on the buffer capacity. SN Send data packet to other neighboring node (In_1) in the route path. Only neighboring node In_1 has enough buffer size to store the packet. Otherwise, the transmitted packets get discarded. The normalized buffer sizes (BR_S) is estimated as given below

$$BR_S = \frac{\text{Number of packet in queue}}{S_b \text{ at node } In_1} \quad (8)$$

The value of BR_S ranges from $[0, 1]$, that indicates nodes' traffic information. In order to minimize the traffic and congestion packets are forwarded towards unloaded node. A source node

selects neighbor nodes and a small queue length or buffer space. When the buffer overflows or the number of incoming packets exceeds then the available buffer space congestion occurs.

The other metric is the bandwidth capacity of each link between the nodes along the end-to-end path. Bandwidth capacity is referred as the maximum number of data packet transmitted from one node to another over path in a specified amount of time. Bandwidth capacity is formulated by,

$$bw_c = \frac{\text{Amount of data packet transmitted}}{t} \quad (9)$$

Where, bw_c denotes a Bandwidth capacity, t indicates a time. The bandwidth capacity is calculated in bits per second.

Rocchio classifier is employed for assigning path to label of the class whose value (i.e. buffer space and bandwidth capacity) is closest to the observation (i.e. best route). Here, the classifier finds the best route as follows,

$$w = \begin{cases} \text{if } [(arg \min BR_S) \&\&(arg \max bw_c)] & ; \text{select best route} \\ \text{otherwise} & ; \text{select another route} \end{cases} \quad (10)$$

Where w represents the output of weak learner, $arg \min(BR_S)$ denotes an argument minimum of buffer space, $arg \max bw_c$ denotes an argument maximum of bandwidth capacity. This describes that the path that has minimum buffer space and the maximum bandwidth capacity is chosen as the best route path among the multiple paths. Next, source node performs data transmission on route path for enhancing data delivery and reducing packet loss due to congestion.

In strong classification results, weak learner results is combined

$$Z = \sum_{k=1}^b w_k \quad (11)$$

Where, Z represents the output of the ensemble learning, w_k indicates the output of weak learners. Next, weight (β) are initialized to weak learner results.

$$Z = \sum_{k=1}^b w_k \beta \quad (12)$$

After the initialization, the error is calculated for every weak learner. It is measured for as given below,

$$Error = [Act_{outcome} - pred_{outcome}] \quad (13)$$

Where, Act_{result} indicates actual outcomes of the weak learner, $pred_{outcome}$ represents the predicted classification outcomes. The ensemble technique detects weak learner's results with lesser error as a final classification result. This helps to accurately find the best route path among the multiple paths to prevent traffic congestion and minimize the delay. The algorithmic process of the Rocchio weighted adaptive robust boost congestion data delivery in WSN.

// Algorithm 2 Multivariate Rocchio adaptive robust boost Congestion aware data delivery
Input: Multiple route paths $r_1, r_2, r_3 \dots, r_m$
Output: Congestion aware data delivery
<ol style="list-style-type: none"> 1. Begin 2. Construct 'k' weak learners 3. For each r_i 4. Measure the buffer space 'BR_S'. 5. Measure the bandwidth capacity 'bw_c' 6. if $[(arg\ min\ BR_S) \ \&\&\ (arg\ max\ bw_c)]$ then 7. select the route 'r_i' as best for data delivery 8. else 9. select the route 'r_j' for data delivery 10. else if 11. Combine all weak learner results $Z = \sum_{k=1}^b w_k$ 12. for each weak learner 'w_k' 13. Initialize the weight 'β' 14. Measure the error '$Error$' 15. end for 16. Update the weight ∇w 17. Find the weak learner results with minimum error 18. Return (strong classification results) 19. Obtain the best route path for data delivery end

Algorithm2 represents the process of Multivariate Rocchio adaptive robust boost ensemble method for predicting disease with improved accuracy and lesser error. The boosting ensemble classifier primarily creates a set of weak learners as the Multivariate Rocchio classifier with the training samples. After that, the weak learner analyzes the estimated buffer space and the bandwidth capacity. Based on this, the weak learner finds the best route for data delivery from source to sink node. In order to obtain strong classification results, weak learner outcomes are combined and the weight is assigned. Thus, training error is measured for every weak learner. The initial weight is updated and finds strong learner with minimum error rate.

4. Simulation Settings

The simulation of TFSVR-MRRBC method and existing ECAR [1] JDRP [2] technique is developed using NS2.34 network simulator. In WSN, 500 sensor nodes are assigned in squared area

(1100 m * 1100 m). Random Waypoint model is employed as mobility model to improve the energy-efficient routing. Sensor node is traveled in the network with a speed of 0 to 20m/sec. The time is set as 300 sec for total simulation. In WSN, the Dynamic Source Routing (DSR) protocol was implemented in energy-efficient routing. Table 2 shows the simulation parameters settings.

Table 2 - Simulation Parameters Settings

Simulation parameters	Values
Network Simulator	NS2.34
Simulation area	1100 m * 1100 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 – 20 m/s
Simulation time	300sec
Routing Protocol	DSR
Number of runs	10

5. Performance Results and Discussion

In this section, performance analysis of proposed TFSVR-MRRBC method and existing ECAR and JDRP technique is discussed by various metrics namely energy consumption, packet delivery ratio, packet drop rate, end to end delay. With help of table and graphical representation, performances of various methods are analyzed. The parameters are described as given below,

5.1. Impact of Energy Consumption

Energy consumption is measured as number of energy consumed by nodes for delivering data packets from one to another node. Energy consumption is calculated as given below,

$$EC_n = \text{Number of sensor node} * EC (\text{single SN}) \quad (14)$$

Where, EC_n represents the energy consumption, ‘single SN’ denotes single sensor nodes. Energy consumption is calculated in joule (J).

Table 3 - Comparison of Energy Consumption

Number of sensor nodes	Energy consumption (Joule)		
	TFSVR-MRRBC	ECAR	JDRP
50	12	13	14
100	14	16	18
150	16	18	20
200	20	23	24
250	24	26	28
300	27	29	31
350	29	32	34
400	31	33	36
450	32	35	38
500	33	36	39

Table 3 provides the performance results of energy consumption versus to number of sensor nodes distributed in squared area (1100 m * 1100 m). The above table illustrates the energy consumption of three different methods TFSVR-MRRBC technique, ECAR [1] JDRP [2]. Among three methods, the TFSVR-MRRBC technique reduces the energy consumption during data transmission. This is proved through statistical analysis. Let us consider the 50 nodes deployed in network and initial energy level of each sensor node was set to 0.5Joule. Due to the transmission process, the primary energy level of sensor node is degraded. Therefore, the energy consumption of the TFSVR-MRRBC technique using 50 sensor nodes is 12Joule. whereas, the energy consumption of the ECAR [1] JDRP [2] is observed as 13Joule and 14 Joule respectively. Similarly, a variety of results are detected by applying the various input. With existing techniques, results are compared. The average of results demonstrates the overall energy consumption using proposed TFSVR-MRRBC technique is comparatively decreased by 9% and 16% when compared to other ECAR and JDRP.

Figure 6 - Graphical Representation of Energy Consumption

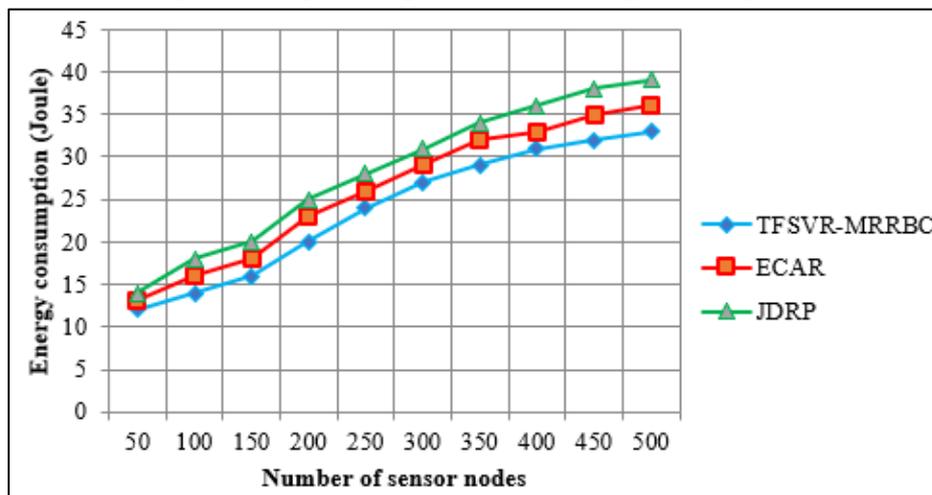


Figure 6, describes the performance of energy consumption associated with Proposed TFSVR-MRRBC technique and existing ECAR and JDRP methods. The x -axis denotes various amount of sensor nodes, while y -axis designates energy consumption of sensor nodes during data transmission. The proposed TFSVR-MRRBC technique minimizes energy consumption. By applying Triangular Fuzzified Support Vector Regression, energy-efficient nodes are chosen. The energy-efficient node is used for data transmission for improving network period.

5.2. Impact of Packet Delivery Ratio

Packet delivery ratio is measured as ratio of the amount of data packets that are effectively delivered to total amount of data packets. It is expressed as given below,

$$packet\ delivery\ ratio = \left[\frac{Number\ of\ packet\ delivered}{Number\ of\ packets\ sent} \right] * 100 \quad (15)$$

The packet delivery ratio is calculated in percentage (%).

Table 4 - Comparison of Packet Delivery Ratio

Number of packets	Packet delivery ratio (%)		
	TFSVR-MRRBC	ECAR	JDRP
30	83	80	77
60	88	85	83
90	91	88	86
120	89	86	83
150	90	87	84
180	88	84	82
210	90	87	83
240	89	85	82
270	90	87	84
300	89	85	83

The table 4 shows the performance results of packet delivery for all methods. The packet delivery ratio is measured as numbers of packets are considered as input in the ranges from 30 to 300. For each method, ten results are observed with various amounts of data packets. The proposed TFSVR-MRRBC method enhances packet delivery ratio while comparing with existing techniques. From source to destination, simulation is conducted with 30 data and 25 data is successfully delivered at destination and the delivery ratio is +found to be 83% using the TFSVR-MRRBC technique. The delivery ratio of ECAR [1] JDRP [2] is obtained as 80% and 77% respectively. The average of ten results denotes data packet delivery ratio is found to be better using the TFSVR-MRRBC technique.

The average of ten results denotes data delivery ratio is significantly improved by 4% and 7% than the conventional techniques.

Figure 7 - Graphical Representation of Packet Delivery Ratio

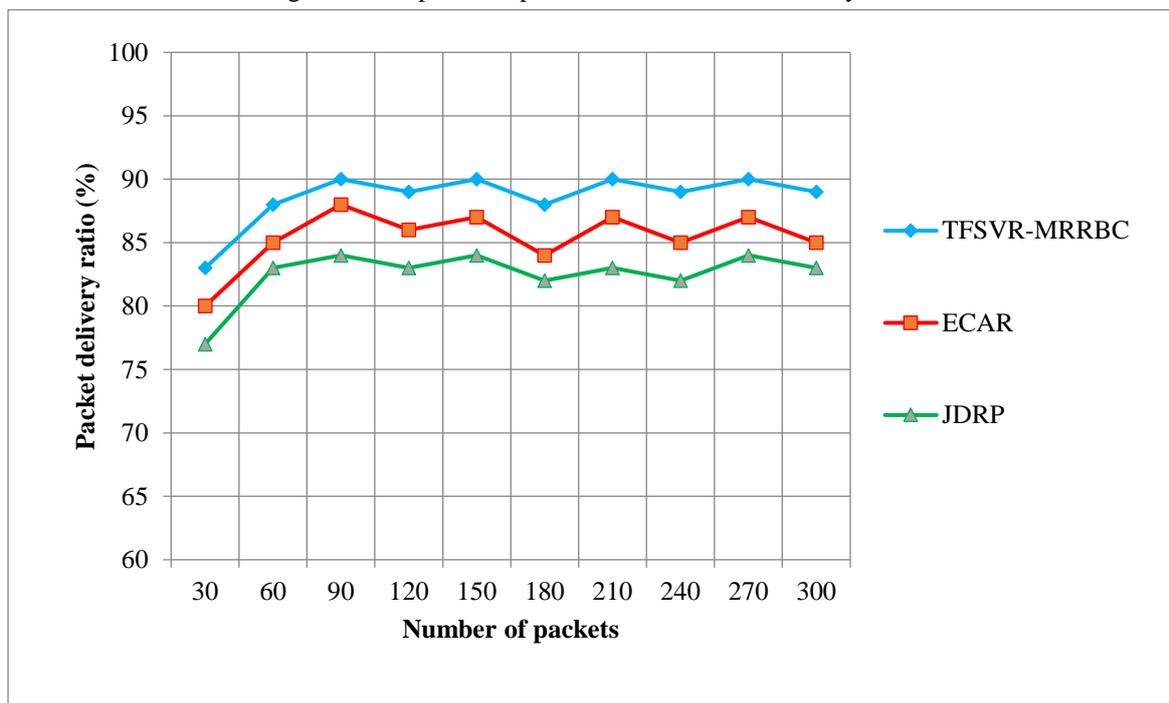


Figure 7, describes the performance evaluation of packet delivery ratio versus amount of data packets ranges from 30 to 300. In figure 4, the amount of data packets in horizontal axis while the delivery ratio is observed in the vertical direction. The graphical chart designates that the TFSVR-MRRBC technique increases data delivery ratio than other two existing methods. The Multivariate Rocchio adaptive robust boost technique finds the best route based on the buffer space and bandwidth capacity. This improve better packet delivery ratio in WSN.

5.3. Impact of Packet Loss Rate

Packet loss rate is evaluated as ratio of amount of packets is lost to total number of packets. Packet loss rate is mathematically formulated as given below

$$packet\ loss\ rate = \left[\frac{Number\ of\ packet\ lost}{Number\ of\ packets\ sent} \right] * 100 \quad (16)$$

The packet loss rate is calculated in percentage (%).

Table 5 - Comparison of Packet Loss Rate

Number of packets	Packet loss rate (%)		
	TFSVR-MRRBC	ECAR	JDRP
30	17	20	23
60	12	15	20
90	10	12	16
120	11	14	17
150	10	13	16
180	12	16	18
210	10	13	17
240	11	15	18
270	10	13	16
300	11	15	17

Table 5 given above reports the packet loss rate respect to number of data packets ranges from 30 to 300. During data transmission, packet loss rate is calculated. From the observed results, the TFSVR-MRRBC technique minimizes the packet loss rate while compared to existing methods. From source node 30 data packets being sent and 5 data packets is lost with percentage 17% using TFSVR-MRRBC technique, and loss rate of existing methods ECAR and JDRP are 20% and 23%. The TFSVR-MRRBC technique is compared with existing techniques. The average assessment results shows that packet loss rate of TFSVR-MRRBC technique is considerably reduced with 22% and 36% while compared to existing ECAR and JDRP.

Figure 8 - Graphical Representation of Packet Loss Rate

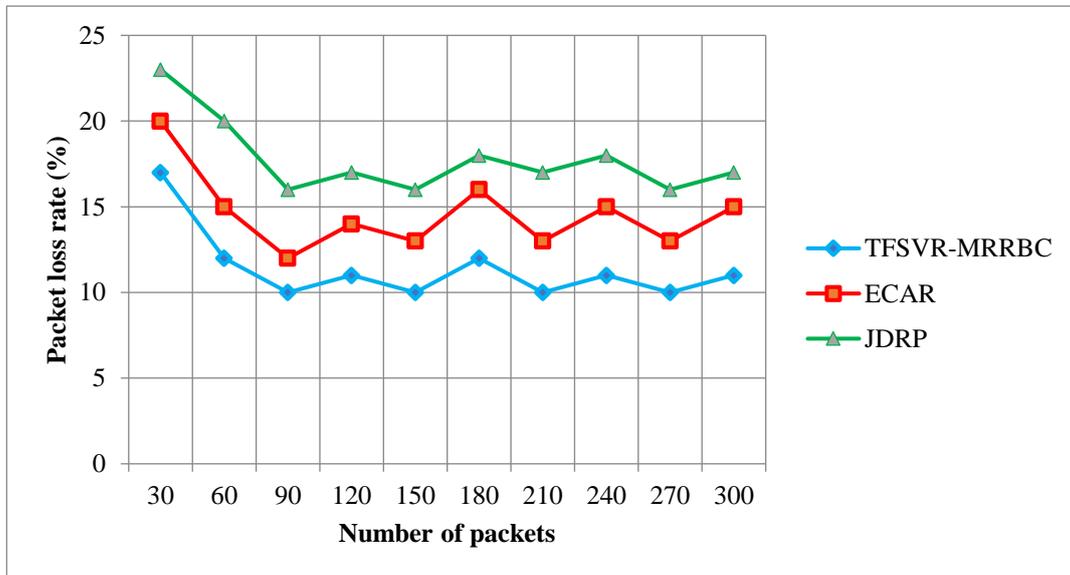


Figure 8 demonstrates the packet loss rate of three methods versus amount of data packets. The TFSVR-MRRBC technique minimizes loss rate with existing techniques. The major reason is to perform the congestion-aware data delivery. The TFSVR-MRRBC technique finds the Multivariate Rocchio adaptive robust boost technique finds the minimum buffer space and the maximum bandwidth route to deliver the multiple packets from source to sink node. Due to congestion, data delivery is improved and loss is reduced.

5.4. Impact of End to end Delay

It is referred as difference among expected arrival time and actual arrival time of packet. The overall delay of data transmission is calculated as given below,

$$ETED = [At_{actual}] - [At_{Expected}] \quad (17)$$

Where ‘*ETED*’ is the end to end delay, *At_{actual}* indicates the actual arrival time and ‘*At_{Expected}*’ represents the expected arrival time. It is calculated in millisecond (ms).

Table 6 - Comparison of End to end Delay

Number of packets	End to end delay (ms)		
	TFSVR-MRRBC	ECAR	JDRP
30	13	15	17
60	15	17	19
90	17	20	22
120	18	22	24
150	20	24	26
180	22	26	28
210	25	27	30
240	27	30	32
270	29	32	34
300	31	33	35

Figure 9 - Graphical Representation of End to end Delay

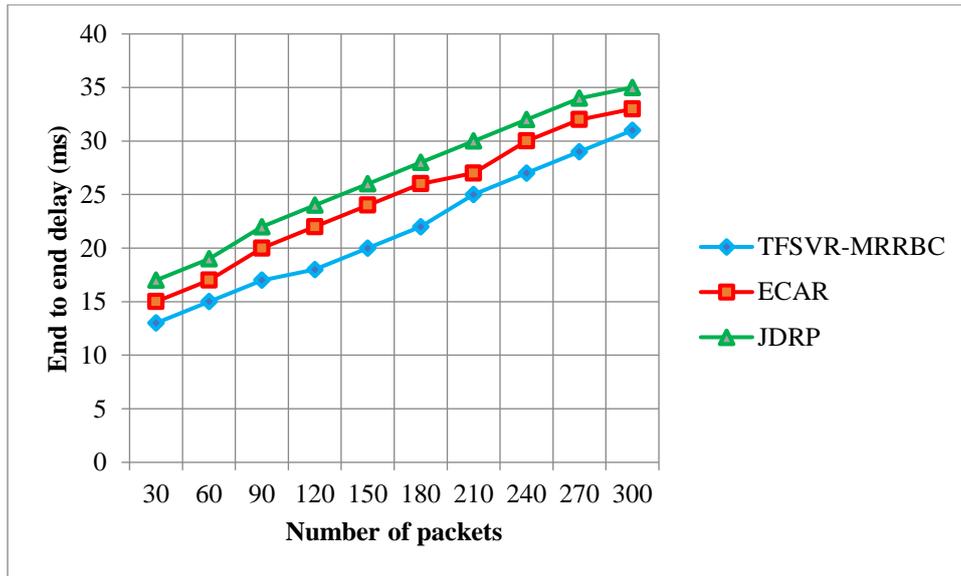


Table 6 and figure 9 shows simulation results of end-to-end delay of data transmission versus to amount of data packets ranges from 30 to 300. The graphical chart demonstrates the proposed TFSVR-MRRBC technique and existing ECAR and JDRP methods. In figure 9, amount of data packets in horizontal axis and delays of three methods are observed in vertical axis for different amount of data packets. In graph, end-to-end delays of the data transmission get increased as improving the amount of data packets. However, the simulation is accomplished for 30 data packets, data delivery is ‘13ms’ using TFSVR-MRRBC technique and, the overall delay using ECAR [1] JDRP [2] was observed to be 15ms and 17ms. Similarly, the other nine results are obtained with the input counts from 60, 90, 120, 150, 180, 210...300. The observed result of proposed TFSVR-MRRBC method is compared with existing methods. The overall results confirmed the delay using TFSVR-MRRBC technique is considerably reduced by 12% when compared to [1] and 20% when compared to [2]. The major reason for this improvement is used for detecting energy-efficient nodes for route path construction. Besides, the route path having maximum bandwidth and minimum buffer space is selected for minimizing the network traffic and avoid congestion. This reduces end-to-end delay of data delivery.

6. Conclusion

A novel congestion-aware data delivery technique is called TFSVR-MRRBC which is introduced by an energy-efficient route discovery mechanism for selecting best route in WSN. The proposed TFSVR-MRRBC technique initially identifies the energy-efficient nodes for route path construction with the help of the Triangular Fuzzified Support Vector Regression. As a result, the

energy-efficient routes are identified between sources and sink node during control message distributions. After the route path finding, the best route path is identified using Multivariate Rocchio adaptive robust boosting for congestion aware data delivery based on the buffer space and bandwidth capacity. The selected best route is used to deliver the packets with minimum delay. Experimental analysis is performed for evaluating the proposed TFSVR-MRRBC technique with conventional routing algorithms through different parameters namely energy consumption, packet delivery ratio, packet loss rate, and end-to-end delay. The validated result shows that the proposed TFSVR-MRRBC technique provides better results having a higher delivery rate, and lesser loss rate, delay as well as energy consumption than the conventional methods.

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