Improvement of Packet Delivery Ratio in MANET Using ADLR: A Modified Regularization-Based Lasso Regression

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***Abstract*—Mobile Ad hoc Networks (MANETs) are characterized by their dynamic topology, limited bandwidth, and unpredictable link conditions, which make reliable packet delivery a significant challenge. Regression techniques have been previously utilized in Mobile Ad hoc Networks (MANET) with a high success rate. However, a modification of Lasso regression is still required to effectively mitigate attacks while improving service quality. In our research paper, we developed an innovative method that integrates a modified Lasso regression analysis with a regularization term based on absolute deviation. By comparing the modified Lasso regression algorithm with other regression techniques, such as linear regression, ridge regression, Least Absolute Deviation (LAD) regression, Method of Least Square (MLS) regression, and Ridge regression, we demonstrate its superior performance over the others. During the Wormhole attack, we attempted to enhance the packet delivery ratio, reduce delay variance, etc., using our algorithm. It was discovered that the Absolute Deviated Lasso Regression (ADLR) algorithm outperformed others significantly when dealing with large datasets. Through experimental evaluation, we have demonstrated that our modified algorithm significantly reduces errors and maximizes the packet delivery fraction by more than 90% compared to other regression techniques. The highest packet delivery ratio reaches 92%, while the lowest packet loss ratio is 24% when using our ADLR algorithm.**

***Keywords*—Adhoc on Demand (AODV), Packet Delivery Ratio (PDR), throughput, wormhole**

I. Introduction

Mobile Ad hoc Networks (MANETs) [1] have emerged as a promising solution for communication in dynamic and infrastructure-less environments. They are characterized by the absence of fixed infrastructure, allowing devices to establish wireless connections [2] and form a self-regulating network.

MANETs find applications in scenarios such as disaster management [3], military operations [4], and sensor networks [5]. However, the dynamic nature of Mobile Ad hoc Networks (MANETs) challenges reliable packet delivery [6]. Due to factors such as node mobility [7], varying link quality [8], and limited bandwidth [9], ensuring efficient and robust communication becomes a critical concern.

Various strategies have been suggested to enhance the efficiency of packet delivery in Mobile Ad hoc Networks (MANETs). These include routing protocols, congestion control mechanisms, and methods for estimating link quality.

In recent years, machine learning algorithms [10], especially regression analysis [11], have gained attention for their potential to optimize network performance in Mobile Ad hoc Networks (MANETs) [12]. Regression analysis provides a method to model the relationship between input features and the desired output, enabling prediction and decision-making. Among the regression techniques, Lasso regression [13] has demonstrated effectiveness in feature selection and regularization, enabling accurate predictions in high-dimensional datasets.

Packet Delivery Ratio (PDR) [14] in a Mobile Ad hoc Network (MANET) refers to the ratio of the number of packets successfully delivered to their intended destination to the total number of packets sent by the source node.

In Mobile Ad hoc Networks (MANETs), where nodes interact directly without relying on a fixed infrastructure, packet delivery can be challenging due to dynamic network conditions, such as node mobility, limited transmission range, and interference. The PDR [15] metric helps measure the effectiveness and reliability of packet transmission in such networks. In computing the packet delivery ratio, it is essential to monitor both the total number of packets dispatched by a source node and the number of packets effectively received by the destination node. Delay variance, also known as Packet Delay Variation (PDV) or jitter [16], is a metric used to measure the variation or fluctuation in the delay experienced by packets as they traverse a Mobile Ad Hoc Network

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(MANET). In a Mobile Ad hoc Network (MANET), packets may encounter different paths and experience varying delays due to factors such as node mobility, network congestion, varying transmission ranges, and route changes.

Delay variance [17] is typically calculated based on the timestamps recorded at the sender and receiver for a series of packets. Minimizing delay variance helps maintain a consistent quality of service and ensures smooth delivery of time-sensitive packets within a Mobile Ad hoc Network (MANET) [18].

The rest of the paper is organized as follows. Section II presents the background of our work and related work in the literature. We present our proposed algorithm in Section III. The dataset is described in Section IV. The results and implementations of the algorithm is introduced in Section V. Finally, Section VI concludes our paper.

II. Literature Review

Least squares regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables [19]. It is a widely used method for estimating the coefficients of a linear regression model.

Ridge regression, also known as Tikhonov regularization, is a linear regression technique that addresses the issue of multicollinearity (high correlation) among the independent variables in a regression model [20]. Itis an extension of Ordinary Least Squares (OLS) regressionthat introduces a regularization term to the loss function. This helps reduce the impact of multicollinearity and enhances the stability of the model.

Lasso regression [21], short for Least Absolute Shrinkage and Selection Operator, is a regularization technique used in linear regression models. Similar to ridge regression, Lasso regression aims to address the issue of multicollinearity and enhance the performance and interpretability of the regression model. Motivated by the benefits of Lasso regression [22], this research aims to further enhance the packet delivery ratio in MANETs by introducing a modified Lasso regression analysis. The proposed modification includes an absolute deviation-based regularization term [23], which considers the dynamic and unpredictable nature of MANETs. By considering the absolute deviation, we aim to enhance the robustness and generalization capability of the regression model.

The Least Absolute Deviation (LAD) regression [24] is a powerful statistical approach that provides an alternative to traditional data analysis methods. Unlike the widely used mean-based measures, such as variance and standard deviation, which heavily rely on the assumption of normality, the absolute deviation approach offers robustness against outliers and non-normal distributions. The research focuses on developing a two-step algorithm to implement modified Lasso regression analysis in Mobile Ad hoc Networks (MANETs). The first step involves computing feature factor metrics that capture key characteristics of the network topology, such as node density, signal strength, and connectivity. These metrics serve as inputs to the modified Lasso regression, enabling accurate prediction of packet delivery behavior.

The second step of the algorithm involves updating the iterations to refine the model's accuracy and effectiveness. From Fig. 1, this is obvious that by iteratively optimizing the regression model, the main aim is to minimize errors and maximize the packet delivery fraction [25], thereby enhancing the overall performance of MANETs.

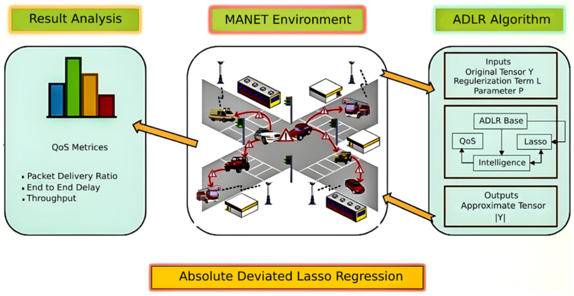

Fig. 1. Improved QoS of MANET using modified lasso regression (ADLR).

To evaluate the performance of the proposed algorithm, it is compared with existing regression techniques commonly used in MANETs. Through extensive experimental analysis, we demonstrate that our modified Lasso regression algorithm outperforms alternative methods in terms of minimizing errors and maximizing packet delivery fraction by more than 90%.

In 2021, Durr-e-Nayab *et al.* [26] published Machine Learning (ML) techniques to optimize network performance by selecting appropriate routing parameters and protocols. The approach involves regressing parameters in a network scenario to achieve optimal results. The network training process is based on a parametric setup that combines the expanding range in the network to estimate key performance metrics such as network throughput, End-to-End (E2E) delay, and Packet Delivery Ratio (PDR) through this training.

Ilango *et al.* [27] proposed a Deterministic Multicast Link-Based Energy-Optimized Routing (DML-EOR) algorithm, designed to achieve efficient data packet transmission in Mobile Ad hoc Networks (MANETs). The DML-EOR mechanism starts by using Deterministic Link stability estimation to identify stable routes from the source to the destination, thereby improving the Packet Delivery Ratio and reducing the average end-to-end delay.

Utilizing a hybrid model by Farheen *et al.* [28] in 2022, a node location prediction technique that considers temporal and spatial characteristics within the neighborhood to estimate probable locations. The estimated probable locations are incorporated into a multi-path routing protocol, enhancing routing performance without adding significant packet overhead.

Patel *et al.* [29] investigated various techniques for predicting multiple link failures. They introduced a novel statistical approach based on least-squares polynomial regression to estimate link failure time in Mobile Ad hoc Networks (MANETs).

Mahalakshmi *et al.* [30] introduced the Fuzzy Linear Regression Method for Link Failure (FLRLF) to determine optimal routes in the context of MANET-Internet of Things (IoT).

Jhaveri *et al.* [31] proposed an advanced proactive secure routing mechanism, as an improvement over the authors' previous scheme. The proposed approach utilizes a linear regression mechanism to forecast the maximum destination sequence number that neighboring nodes can insert into the RREP packet. This prediction helps enhance the security of the routing process.

Yang *et al.* [32] utilized ten-fold cross-validation to validate the Lasso regression regularization coefficient method. Experimental results demonstrate that the model coefficients have been effectively reduced from the initial 125 to just 28, resulting in a significant 78% reduction.

The primary objective of this study is to predict link failures and enhance routing efficiency in MANETs. The Fuzzy Linear Regression Method (FLRM) is used to assess the longevity of links by considering their likelihood of failure. By doing so, the proposed approach aims to optimize route selection and improve the overall performance of MANET-IoT networks.

III. PROPOSED METHODOLOGY

Tensor decomposition serves as a valuable approach for analyzing high-dimensional data. To delve into the specifics of this algorithm, we commend exploring the relevant literature authored by Kolda.

$$\mathrm{Y} \approx \mathrm{Y}' = [\mathrm{U1}, \mathrm{U2}, \mathrm{U3}, \ldots, \mathrm{U}n]\ (n = 1, 2, 3, \ldots, n) \quad (1)$$

Tensor decomposition is an intricate model, and in many cases, increased complexity can result in over fitting, potentially hindering the model's ability to make accurate predictions for future observations. To address this challenge, it's advisable to incorporate a regularization term into the loss function when dealing with more intricate learning tasks. A commonly employed regularization technique involves applying Ridge regression to each of the factor matrices within the tensor. This regularization approach can help strike a balance between model complexity and generalization.

Least Absolute Shrinkage and Selection Operator (Lasso) regression is a regression model that employs the $L1$ norm, denoted as ||W||1. This norm is defined as the sum of the absolute values of each element within the weight vector, W. In the context of feature selection, the

$L1$ norm plays a crucial role by facilitating the minimization of the objective function. It accomplishes this by driving certain elements of the weight vector, W, to zero, effectively eliminating irrelevant or redundant features and reducing their impact on sample predictions. The objective function for Lasso regression incorporates the $L1$ norm, as depicted in the equation below.

$$\mathrm{Y1} = \sum \mathrm{a} = 1\mathrm{b} \sum \mathrm{c} = 1\mathrm{d} \sum \mathrm{e} = 1\mathrm{f} |\mathrm{Yace}| \quad (2)$$

Ridge regression is a regression technique that incorporates the $L2$ norm, denoted as ||Y||2, into its model. The sum of the squares for each element in the parameter vector, Y, is determined by this norm. It promotes each element of W to be relatively tiny and go closer to zero in this way. Smaller model parameters result in a simpler model, and overfitting is less likely when a model is simpler. The optimization procedure in ridge regression entails modifying the objective function by adding a penalty term equal to the squared values of the coefficients., as depicted in Eq. (3).

$$\mathrm{Y2} = \sqrt{\sum \mathrm{a}} = 1\mathrm{b} \sum \mathrm{c} = 1\mathrm{d} \sum \mathrm{e} = 1\mathrm{fY2ace} = \sqrt{(\mathrm{Y}, \mathrm{Y}')} \quad (3)$$

The process of computing an approximate tensor to fulfill the given equation can be framed as an optimization problem. Among the various optimization algorithms for tensor decomposition, the Alternating Least Squares (ALS) algorithm stands out as one of the most widely employed methods. ALS operates by optimizing one of the decomposition elements while maintaining the others at a fixed state during each iteration. Specifically, ALS iteratively refines the factor matrices (n) by minimizing a loss function through the method of least squares.

For an original tensor Y and approximation tensor Y′, the goal is to minimize the loss function L.

$$\mathrm{L} = ||\mathrm{Y} - \mathrm{Y}'||2 + \lambda\Omega(\mathrm{Y}') \quad (4)$$

The tensor decomposition of the regularization term consists of the overfitting issue, which is why it fails to deliver the best performance. To overcome this, we have applied the absolute deviation-based approach and developed the new modified equation:

$$\Omega(|\mathrm{Y}|)\mathrm{New} = \lambda(1 - \frac{p}{2||\mathrm{Mod(Y)}||2} + p\big|\big|\mathrm{Mod(Y)}\big|\big|1 \quad (5)$$

where |Y| denotes the absolute approximation tensor, ||.|| denotes the tensor norm, $\lambda > 0$.

L(Y,|Y|) is performed as shown in Eq. (6).

$$\mathrm{MinL}(\mathrm{Y}, |\mathrm{Y}|) = \min(||\mathrm{Y} - |\mathrm{Y}|||2 + \lambda\Omega(|\mathrm{Y}|)\mathrm{New}) \geq \min(||\mathrm{Y} - |\mathrm{Y}|||2) + \lambda(1\mathrm{p}/2(||\mathrm{U}(1)||2 + (||\mathrm{U}(2)||2 + \cdots + (||\mathrm{U}(n)||n) + \mathrm{p}(||\mathrm{U}(1)||2 + (||\mathrm{U}(2)||2 + \cdots + (||\mathrm{U}(n)||n)) \quad (6)$$

where, Un, n = 1, 2, …, n denotes regular factor.

Algorithm 1 describes the function of the modified lasso regression term.

Algorithm 1: Absolute Deviated Lasso Regression with a Modified Regularization Term

Input: An original Tensor Y, regularization term λ,
And parameter p.
Output: An approximate Tensor, |Y|.
Set values of U1, U2, …., Un (n = 1, 2, 3, …, n)
If (λΩ=|Y|)
Update value of |Y|
Else
(L(Y,|Y|)Reduced=||Y−|Y|||2+λΩ(|Y|).
For (|Y| >= λΩ(|Y|))
Return
value(|Y|)
end if
end for

IV. Dataset Description

The information provided in this paragraph pertains to data collection within a network segment at The University of Cauca, Colombia. The data-gathering process involved conducting packet captures during various timeframes, including both morning and afternoon sessions, spanning over six specific days in 2017: April 26, 27, 28, and May 9, 11, and 15. The data set in question encompasses a comprehensive set of 87 distinct features. Each instance within this dataset carries specific details regarding an IP flow generated by a network device. These details encompass essential information such as the source and destination IP addresses, port numbers, inter-arrival times, and the layer 7 protocol (which denotes the application) utilized in that particular flow, among other relevant attributes. It's noteworthy that while the majority of these attributes are of numeric type, there are also nominal types and a date type attributed to the Timestamp field, ensuring a diverse and multi-faceted dataset.

From so many features, we have mainly taken the total number of packets, the Number of forwarded packets, forwarded average. packet size, forwarding mean inter-arrival time, and packet delivery ratio.

A. Dataset Features

Total Packets: The total number of packets in the dataset for a specific network and IP address as of 2017 is recorded.

Then, this is set aside for final evaluation. Here, we have a maximum of 1,000,000 data packets.

1. Forwarded Packets: The total number of packets forwarded from the source node to the destination node isconsidered the final input.
2. Forwarded Average Packet Size: The average packet size between two nodes is 1,000 bytes.
3. Mean Inter-Arrival Time: The time taken to travel from the source node to the terminal node is calculated, and then the meantime is estimated.
4. Packet Delivery Ratio (PDR): This is calculated by dividing the total number of packets sent by the total number of packets received.

B. Testing of Data with Algorithm

After pre-processing, all the null values have been removed from our dataset. The features were extracted and trained using our algorithm in Python within the Anaconda distribution. Our revised algorithm processes input from the original tensor and generates an estimated tensor value as output. The weight factor Y is updated in our algorithm using $|Y - Y'|$, which represents the absolute deviation value.

V. Results and Discussions

After receiving the data packets, the packets are forwarded and Fig. 2 describes the forwarded data packets with average size. Fig. 3 describes the mean inter-arrival time taken by the data packets to be reached. Features of packets sent are represented along the X-axis, where the packet delivery ratio is represented along the Y-axis. After that, we applied our modified Absolute Deviated Lasso Regression technique and then compared the different QoS results of MANET with the results received by applying Ridge Regression, LAD Regression, and MLS Regression also. The packet delivery ratio was much improved using our modified algorithm. Also, the delay variance became lesser than the other unconventional approaches, and energy efficiency also proved to be much better than the conventional approaches.

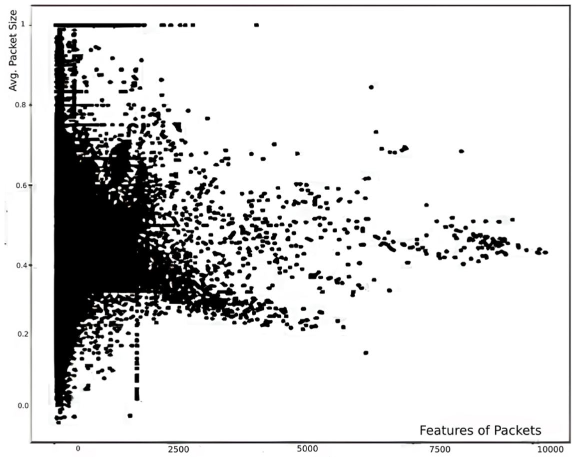

Fig. 2. Forwarded Avg. packet size.

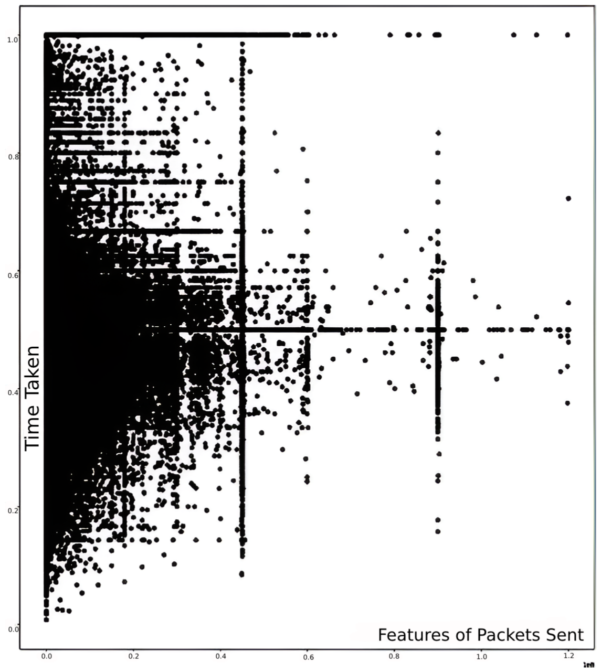

Fig. 3. Mean inter arrival time.

The modified ADLR algorithm is applied which is based on the Lasso regression method with a modification of regularization terms with the help of the absolute deviation statistical approach. After applying the algorithm to the dataset, the graph of the packet delivery ratio from source to destination is constructed. Fig. 4 depicts the ADLR algorithm for the packet delivery ratio. Later on, it is compared that the modified Lasso regression algorithm with the Least Absolute deviation approach, Method of Least Square approach, and Ridge regression in terms of the quality of services of MANET. ADLR algorithm proved to be the best one compared to others as the delivery ratio of data packets from source to destination is much better. Also, energy efficiency and delay variance are much better with our modified ADLR algorithm.

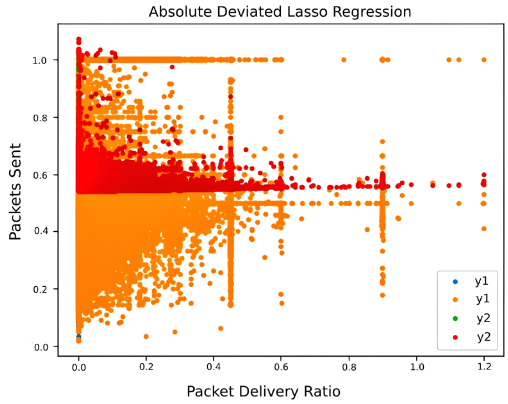

Fig. 4. Packet delivery ratio using ADLR algorithm.

The modified ADLR—Lasso regression algorithm is used in the dataset and found that the number of alive nodes after the attack is much more than compared to the other regression algorithms like Ridge Regression, LAD Regression, and MLS Regression and depicted by Fig. 5.

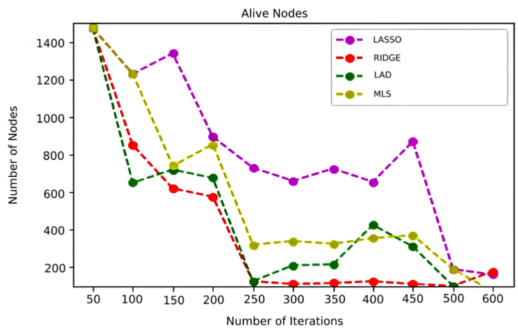

Fig. 5. Number of alive nodes.

Fig. 6 portrays the comparison between the regressions and their energy efficiency after the attack in MANET. The energy efficiency of the modified ADLR algorithm was proven to be the best. Table I consists of the comparison of energy consumption by different algorithms during the attack.

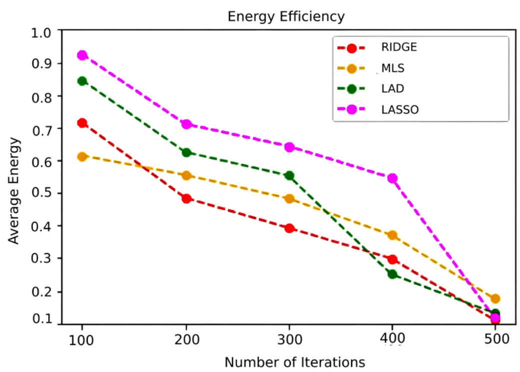

Fig. 6. Energy efficiency.

TABLE I. COMPARISON OF ENERGY CONSUMPTION

No. of Nodes	MLS Regression	Ridge Regression	LAD Regression	ADLR
100,000	30	30	32	30
200,000	35	50	30	20
300,000	38	40	45	25
400,000	35	40	45	25
500,000	25	30	42	20
600,000	35	35	40	25
700,000	25	35	40	26
800,000	35	35	40	25
900,000	32	34	40	22
1,000,000	40	50	40	24

Mobile ad hoc networks always lose energy after mitigation of attacks. The main aim of every researcher is to prepare a manet protocol that is energy efficient. The different approaches to making the energy-efficient MANET are listed below.

Energy-Aware Routing Protocols: Designing routing protocols that consider the energy levels of nodes is crucial. Protocols such as Ad Hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR) aim to minimize energy consumption by selecting energy-efficient paths for data transmission.

Node Power Management: MANETs benefit from effective power management strategies. Nodes can adjust their power levels based on their proximity to neighbors and the communication requirements. This adaptive approach helps conserve energy by reducing unnecessary power consumption.

Sleep Mode for Idle Nodes: Introducing sleep modesfor idle nodes is an effective strategy to conserve energy. Nodes can switch to a low-power sleep mode when not actively participating in communication, reducing the overall energy consumption of the network.

Energy Harvesting: Exploring energy harvesting techniques, such as solar or kinetic energy, can contribute to the sustainability of MANETs. Integrating energy harvesting capabilities into nodes helps offset energy consumption and extend network lifetime.

Quality-of-Service (QoS) Considerations: Energy-efficient protocols should balance energy conservation with meeting application-specific Quality-of-Service requirements. Tailoring solutions to the specific needs of applications ensures a trade-off between energy efficiency and performance.

Dynamic Topology Management: Recognizing the dynamic nature of MANETs, efficient topology management is essential. Nodes can adaptively adjust their connectivity to minimize energy consumption, especially in scenarios where the network topology changes frequently.

Fig. 7 shows the delay variance of the packets sent from source to destination and after our comparison, we have found that our Absolute Deviated Lasso Regression delivered the packets with the lowest delay time. With the increment in the number of packets, our ADLR algorithm proved to delay less than all others. Along the X axis, we have declared the Number of Nodes and along the Y axis, we have declared the Average Delay.

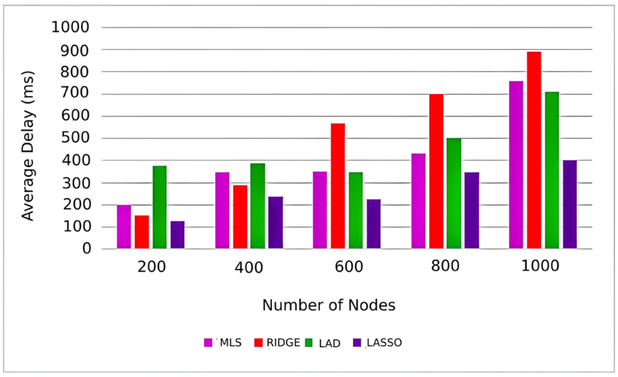

Fig. 7. Delay variance.

$$\text{Packet Delivery Ratio} = \frac{\text{Total Packets Received}}{\text{Total Packets Sent}}$$

Packet Delivery Ratio (PDR) is a crucial metric in Mobile Ad Hoc Networks (MANETs) that assesses the efficiency of data transmission within the network. It represents the ratio of successfully delivered packets to the total number of packets sent. In a MANET, where nodes communicate wirelessly without a fixed infrastructure, PDR becomes a key indicator of the network's reliability and performance. A high PDR implies a robust and effective communication system, indicating that a significant portion of the transmitted data reaches its intended destination successfully. Achieving a high Packet Delivery Ratio in MANETs is essential for applications such as emergency response systems, military communications, and collaborative sensing networks, where timely and accurate information delivery is critical. Researchers and practitioners continually explore and develop routing protocols, adaptive algorithms, and optimization techniques to enhance PDR and overall network performance in dynamic and challenging MANET environments.

After the attack, the number of packets delivered to the destination node from the source node is calculated and also compared the results with other regression algorithms. This result is proved in Table II. From the table, Absolute Deviated Lasso Regression was proved to be the best as this algorithm sent the maximum number of data packets even after the security attacks. Fig. 8 shows the ratio of packet delivery. Along the X-axis, the total nodes are represented, and along the Y-axis, the packet delivery ratio is represented.

TABLE II. PACKET DELIVERY RATIO

No. of nodes	MLS Regression	Ridge Regression	LAD Regression	ADLR
100,000	80	70	85	92
200,000	55	50	65	72
300,000	50	40	55	68
400,000	40	30	48	55
500,000	30	32	35	52
600,000	35	28	45	58
700,000	30	27	38	57
800,000	30	35	25	48
900,000	25	25	22	47
1,000,000	40	50	40	48

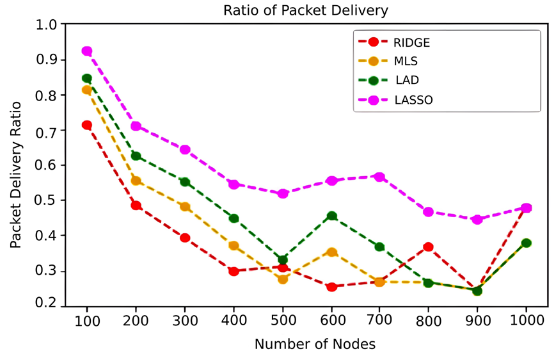

Fig. 8. Packet delivery ratio.

After sending the packets from source to destination, a few of data packets were lost due to the attack. From Table III, it is easily predictable that the modified ADLR algorithm lost the least amount of packets during the attack. So, the modified algorithm was proved to be better than all the conventional algorithms in terms of different quality of services. The ratio of packet loss is shown in Fig. 9.

TABLE III. PACKET LOSS RATIO

No. of Nodes	MLS Regression	Ridge Regression	LAD Regression	ADLR
100,000	60	70	85	92
200,000	59	50	65	75
300,000	55	40	60	70
400,000	45	35	35	60
500,000	20	10	15	10

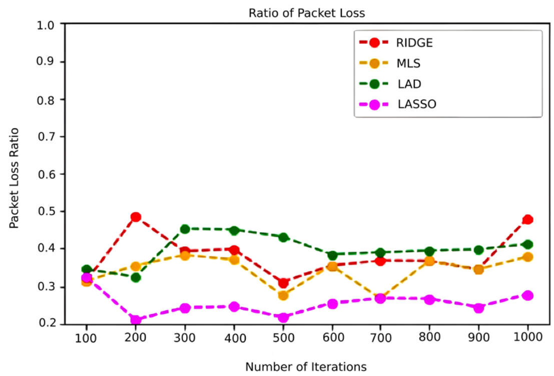

Fig. 9. Packet loss ratio.

VI. CONCLUSION

In conclusion, this research paper addresses the challenges posed by the dynamic topology, limited bandwidth, and unpredictable link conditions in Mobile Ad hoc Networks (MANETs) by introducing an innovative method: the Absolute Deviated Lasso Regression (ADLR) algorithm. This novel approach combines a modified Lasso regression analysis with a regularization term based on absolute deviation. Experimental results demonstrate that the ADLR algorithm outperforms other techniques, achieving a packet delivery fraction of 92% and reducing errors. The number of packets lost during the attack is much reduced using the ADLR algorithm. The number of packets lost during the attack is much reduced using the ADLR algorithm. This research contributes a valuable tool for addressing reliability concerns in MANETs, offering a robust solution to improve service quality in the face of dynamic and challenging network conditions.

Lasso regression tends to exhibit instability in variable selection, especially when dealing with highly correlated predictors. Small changes in the data or slight variations in the model parameters may lead to different subsets of selected variables. The performance of Lasso is highly dependent on the choice of the penalty parameter (lambda). Selecting an appropriate value for lambda can be challenging, and it may require cross-validation, adding an extra layer of complexity to the modeling process.

To solve the limitations, the lasso regression may be modified using the mean deviated parameter (λ'). If the mean value of selected variables is calculated from the dataset, we can fit that as a model parameter of lasso regression. This technique can lead to good results in the future.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Sayan Majumder reviewed the literature, designed the research methodology, collected the results, and compiled the manuscript under the supervision of Debika Bhattacharyya and co-supervision of Subhalaxmi Chakraborty; All authors had approved the final version.

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