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OPTIMIZATION OF BORDER GATEWAY ROUTING PROTOCOL WITH LAGRANGE MULTIPLIER AND GRADIENT DESCENT INTEGRATION FOR NETWORK

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This study has a research object, namely data transmission lines. In this study, there are problems that must be solved related to the optimization of network transmission routes that are dynamic and adaptive to changes in real-time conditions, including latency factors, connection stability, and algorithm integration that can accommodate large-scale network needs efficiently in terms of transmission. The results obtained from this study are in the form of a model that can identify route management and optimize the border gateway protocol. The results of the study show that the application of this method can optimize the transmission path by considering network constraints and real-time condition dynamics. This study has an interpretation that the proposed model is proven to be effective in improving network performance, with increased efficiency, reduced constraints, and the ability to adapt to changes in network conditions. This is evidenced by the accuracy in the form of quantitative effectiveness by producing 95 % accuracy with the Reinforcement Learning model, able to significantly increase efficiency and accuracy compared to traditional methods in BGP routing optimization. The characteristics contained in this study include the ability to manage and identify transmission routes to improve network efficiency, reduce latency, increase throughput, minimize the number of hops in managing BGP transmission routes. There are limitations related to input data processing that require deeper annotation. This study contributes to BGP route optimization with machine learning algorithms that can be applied in complex and dynamic networks

***Keywords:** BGP, connection stability, routing, machine learning, Lagrange multiplier, gradient descent*

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1. Introduction

Currently information and communication technology networks, especially internet networks, have a significant impact on various sectors such as business, education and health. In internet operations there will be a process of managing network components such as Border Gateway Protocol (BGP) [1, 2]. Considering the strategic role of Border Gateway Protocol (BGP) in managing data flows between autonomous networks (Autonomous Systems/AS) throughout the world. In the rapidly developing digital era, the complexity of the global internet network has increased drastically, involving millions of routes and thousands of ASs. Challenges such as route instability, increased latency, transmission failures, as well as the inability of protocols to adapt to dynamic network conditions in real-time are critical issues that affect overall network performance. Traditional BGP approaches, based on static information and fixed routing policies, are no longer adequate to address the needs of the modern era that prioritizes efficiency, stability, and adaptivity. BGP is a routing protocol that regulates the flow of data between autonomous networks (Autonomous Systems/AS) throughout the world. In the BGP process, ensuring data reaches its destination efficiently depends on the protocol's ability to select optimal routes [3, 4]. However, complexity in the network that makes it difficult to process transmission paths and in BGP management such as route instability which can result in slow response times, transmission failures, and increased latency [5, 6]. This instability is influenced by various factors, including network traffic dynamics, hardware failures, and security attacks such as BGP hijacking. On the other hand, routing decisions taken by BGP are often based only on static information, such as route metrics or predefined routing policies, without considering real-time dynamic network conditions. This approach, although reliable at the beginning of the internet era, is increasingly inadequate to meet the needs of the growing digital era [7, 8].

With the development of network technology and increasing data traffic, border gateway protocols are required to be more efficient, which currently face problems such as slow convergence, network traffic congestion, and suboptimal resource usage, so this study proposes the integration of Lagrange Multiplier and Gradient Descent to improve routing efficiency [9, 10]. The Lagrange Multiplier method can optimize the path and consider bandwidth and latency, while gradient descent can accelerate convergence to become optimal [11, 12]. Therefore, research that is specifically designed to reduce latency, increase network stability, and optimize the use of resources that have scientific relevance to the industry is expected to make the network system more adaptive, efficient, and reliable in facing the challenges of the digital era.

2. Literature review and problem statement

Analysis of the study [13] shows that while the potential for ML integration in BGP is enormous, there are several challenges that must be overcome. First, ML applications require large, high-quality data to train the model, which in some cases may be difficult to obtain due to privacy or storage capacity constraints. Second, the ML algorithms used must be designed to be computationally efficient, given that BGP operates in real-time. Gradient Descent, with its variants such as Stochastic Gradient Descent (SGD) and Adam Optimizer, offers an efficient solution through adaptive learning rate settings, making it applicable in real-time BGP environments.

Research [14] performing BGP optimization using machine learning by leveraging Gradient Descent for iterative model updates, has broad impacts beyond the technical domain. In an economic context, increasing routing efficiency can reduce the operational costs of internet service providers (ISPs) which can ultimately be transmitted to consumers in the form of more affordable rates.

Research [15] conducting more reliable network connectivity to support various digital initiatives, including online education, telemedicine, and e-commerce so that it can develop new methods to optimize BGP by utilizing efficient ML algorithms such as Gradient Descent. This method must not only be able to improve route efficiency, but also must be able to overcome existing challenges, both from a technical and operational perspective. Thus, this research will make a significant contribution to the development of future network technologies, while supporting sustainable digital transformation.

Research [16] shows that the results of this research use a prediction model based on a reinforcement learning algorithm to optimize routing efficiency in communication networks. This research highlights that prediction models based on reinforcement learning algorithms face obstacles in responding to changes in network conditions quickly, causing decision making to be delayed. there are problems such as processing time complexity which is the main challenge which has an impact on the speed and scalability of the model. Based on the systematization of the identified local problems, the main problem emerged in the form of how to design a machine learning-based optimization model that can overcome limitations in routing efficiency and processing time complexity, while being able to adapt to changes in network conditions in real-time.

Research [17] uses an unsupervised learning approach to detect anomalies in BGP transmission routes. The problem is that there are still anomalous patterns that occur in networks with high scalability, causing high latency. but there are problems in determining blockchain parameters in machine learning. can be concluded that there are problems with routing efficiency and in terms of protocol security as well as limitations in understanding the complex relationships between network topology variables, especially in large-scale networks. So that common unresolved problems involve problems such as anomaly detection efficiency in large-scale networks, security optimization of blockchain technology-based routing protocols and understanding complex relationships between network topology variables to increase routing processing efficiency.

Research [18] introduces a route clustering algorithm based on k-means clustering to group transmission routes in autonomous networks. In this section there are problems in grouping paths to obtain effective transmission. This problem has not been resolved because many models produce low accuracy, so this research will apply the K-means algorithm so that there is an unresolved problem, especially related to time complexity and decreased latency. Based on this analysis, there will be a problem formulation, namely how to develop a machine learning-based algorithm, especially for BGP routing optimization, which is able to overcome problems in grouping transmission routes, efficiency in setting parameters in the protocol, as well as reducing latency, so that it can optimize the Border Gateway routing protocol in real networks time.

Research [16] reviews policies in static routing with routing that can affect efficiency in bandwidth usage. The problem in this section is the absence of network traffic patterns so that it is difficult to create a bandwidth usage management model so that there are unresolved problems such as the absence of network traffic patterns that cause difficulties in bandwidth management. In the context of this analysis, the problem will be formulated on how to develop a machine learning-based model that can be applied to static routing management to improve bandwidth usage efficiency, overcome low latency and bandwidth limitations, and provide flexibility in dealing with changes in network traffic.

Research [19] explains the route failure prediction model using the support vector machine (SVM) algorithm. The problem in this section is network instability in route management for stable networks so that it is difficult to apply the right algorithm so that the results of the analysis will find unresolved problems such as network instability which causes difficulties in route management and the application of effective algorithms. Models on networks with dynamic topology are a major challenge in routing optimization. These problems will be analyzed to produce problem formulations such as How to develop a machine learning-based model combined with artificial neural networks to overcome network instability problems, connectivity constraints and processing time complexity, so that they can optimize the Border Gateway routing protocol on networks with dynamic varying topologies.

Research [20] provides a comprehensive overview of various control plane development efforts in inter-domain routing protocols, especially Border Gateway Protocol (BGP). This study explores the problems faced by traditional BGP protocols, such as lack of adaptability to network dynamics, security that is vulnerable to attacks (such as BGP hijacking), and routing efficiency which is still an obstacle on a global network scale. In the context of source-based analysis, problem formulations will emerge such as How to apply a machine learning-based model to optimize the Border Gateway (BGP) routing protocol by increasing adaptability, routing efficiency and network security in real-time, especially on global and multi-domain networks.

Research [21] is related to the problems often faced by the BGP routing protocol in terms of efficiency. The results are still not able to optimally run the routing process efficiently so that from the analysis of the problem there will be vulnerabilities in the BGP network so that it is difficult to overcome so that to optimize in terms of efficiency and security in routing protocols will highlight the problem of the evolution of the proposed method to improve efficiency, security, and network adaptability so that there will be unresolved problems such as the multi-domain approach which has potential, but requires a more evolutionary method to cover network efficiency, security, and adaptation.

In research [22], there are obstacles in performing less efficient routing on 5G networks and time complexity. There is a decrease in latency, making it difficult to handle the network in real time, so that there are unresolved problems, namely routing efficiency on 5G networks, especially related to time complexity and latency reduction. Based on this analysis, a problem formulation will arise, namely how to develop a machine learning-based procedure, especially for BGP routing optimization that is able to overcome problems in grouping transmission routes, efficiency in setting parameters on the protocol, and reducing latency so that it can optimize the Border Gateway routing protocol on real-time networks.

3. The aim and the objectives of the study

The aim of this study is to develop a machine learning-based system that can optimize border gateway routing protocols in improving data transmission route management.

To achieve this aim, the following objectives are achieved:

– implementation of gradient descent algorithm to optimize border gateway protocol routing;

– evaluation of the effectiveness against machine learning based models.

4. Materials and methods

This research has a research object, namely data transmission lines. In this study, there is a main hypothesis, namely the use of the Gradient Descent algorithm in managing transmission routes based on the Border Gateway Routing Protocol (BGP) so that it can increase route identification efficiency, optimize network resource usage, and reduce response time. In this study, there are assumptions regarding the work done to form the basis for implementing the Gradient Descent algorithm in optimizing the border gateway routing protocol to manage transmission routes. In the process, network data will be used to train and test machine learning models that include variations in topology and patterns in data traffic, then the Gradient Descent algorithm that has been implemented can produce time-efficient decisions in identifying transmission routes and the Lagrange Multiplier method will be used in optimization. It is also assumed to be effective in dealing with constraints related to network resource management so that the application of machine learning is expected to provide higher efficiency in managing transmission routes on the Border Gateway Protocol (BGP) as a whole. In this study, a simplification is carried out, namely focusing on the application of the Gradient Descent algorithm in optimizing the Border Gateway Routing (BGP) protocol by considering the existing constraints and complexities. This study uses an approach with a machine learning model in order to identify transmission routes efficiently, without requiring network data that is too complex or too many variables that are difficult to process in a short time. In the context of its solution, a machine learning approach will be used combined with the Lagrange Multiplier optimization technique in order to increase the efficiency of route identification and network resource management. This model will have the advantage of processing large-scale and dynamic network data so that it can produce efficient solutions. This study will begin with a framework architecture as in Fig. 1.

In Fig. 1, there will be data that will be used for the process of optimizing the Gradient Descent algorithm where the data will go through a data cleaning process. The following data will be used in Table 1.

Table 1

Research dataset

Node	Initial_Latency	Initial_Packet_Loss	Initial_Throughput (Mbps)
Node_1	48	2,604751656	67
Node_2	38	2,467824317	57
Node_3	24	2,374241899	59
Node_4	17	3,468623134	32
Node_5	30	2,769639746	57
Node_6	48	4,327452453	32
Node_7	28	3,678410465	63
Node_8	32	1,279726423	45
Node_9	20	3,560672895	51
Node_10	20	2,084589746	61
Node_11	33	3,371247967	67
Node_12	45	3,720527724	37
Node_13	49	1,923316757	37
Node_14	33	2,82743458	35
Node_15	12	1,761299451	43
Node_16	31	1,209355503	61
Node_17	11	2,513905694	64
Node_18	33	2,451777087	39
Node_19	39	4,981921963	32

The following is the mathematical formula for algorithm Gradient Descent in processing transmission routes in the border gateway protocol to increase efficiency, constraints and adaptation to dynamics in real time networks. Optimization aims to select routes X_{ij} which minimizes total latency L, maximize throughput T, and minimize the probability of route failure F.

Objective function:

$$\text{Minimize}: J(x) = w_1 \sum_{(i,j)} x_{ij}\hat{L}_{ij} - w_2 \sum_{(i,j)} x_{ij}\hat{T}_{ij} + w_3 \sum_{(i,j)} x_{ij}\hat{F}_{ij}. \tag{1}$$

In (1) there will be x_{ij} which is a decision variable that has a value $x_{ij} \in \{0,1\}$for route selection from nodes i to nodes j. Then on symbols L_{ij} to carry out the latency process in predicting the route from i to j on models while for symbols T_{ij} perform processes on throughput (i, j) and F_{ij} carry out the process of route failure probability (i, j) which is the symbol w_1, w_2, w_3: weights for each parameter and then there will be formulation (2) to see the process of constraint as follows:

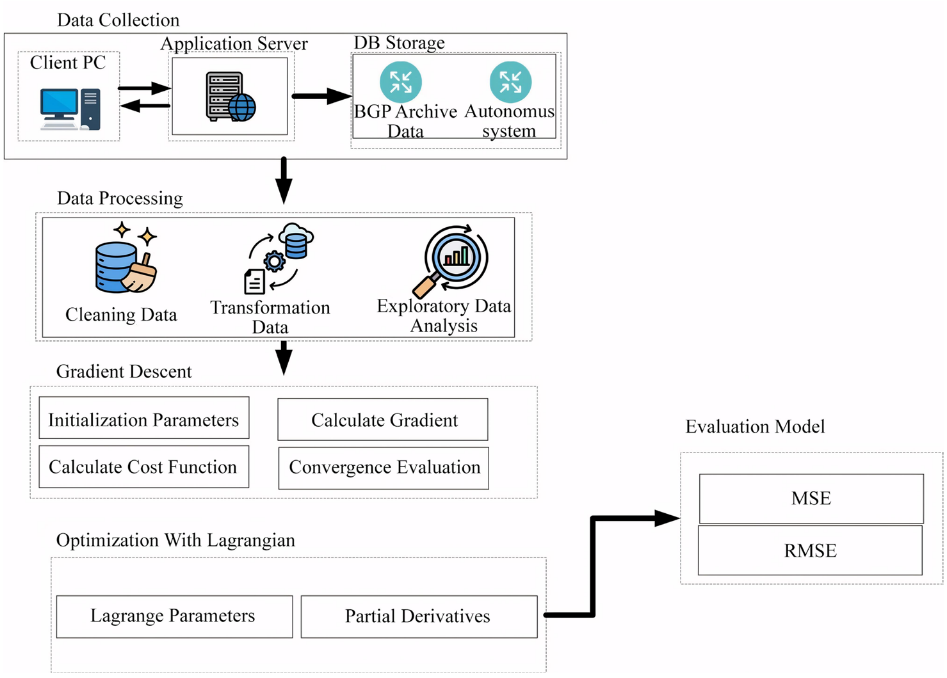

Fig. 1. Proposed architecture

$$\sum_{i} x_{ij} = 1, \forall j. \tag{2}$$

In formulation (2), there will be an entry node and an exit node which will then be processed with formulation (3):

$$\sum_{i,j} x_{ij} b_{ij} \leq C, \ \forall \text{link}. \tag{3}$$

In formulation (3), there will be a symbol b_{ij} which is the route bandwidth (i,j) and C is the total capacity of the links that will be part of the process and in formulation (4) there will be an application of the algorithm:

$$J(x) = w_1 \sum_{(i,j)} x_{ij} \hat{L}_{ij} - w_2 \sum_{(i,j)} x_{ij} \hat{T}_{ij} + w_3 \sum_{(i,j)} x_{ij} \hat{F}_{ij}. \tag{4}$$

In equation (4), there will be a gradient process of the objective function with partial derivatives of X_{ij}:

$$\frac{\partial J}{\partial x_{ij}} = w_1 \hat{L}_{ij} - w_2 \hat{T}_{ij} + w_3 \hat{F}_{ij}. \tag{5}$$

After the process of the objective function on the gradient is complete, variables are updated in the management of route transmission in the border gateway protocol with formulation (6):

$$x_{ij}^{(k+1)} = x_{ij}^{(k)} - \alpha \frac{\partial J}{\partial x_{ij}}^{(k)}. \tag{6}$$

Then after (6) is carried out, the process of the constraint normalization stages will be carried out with X_{ij} to satisfy the constraints as in equation (7):

$$x_{ij}^{(k+1)} = \frac{x_{ij}^{(k+1)}}{\sum_j x_{ij}^{(k+1)}}, \forall i. \tag{7}$$

From equations (1)–(7) it is possible to form a model that can manage transmission routes with the border gateway protocol which produces BGP Routing Optimization Pseudocode:

1. INPUT:
- Initial routes: x[i][j] ∈ [0, 1], randomly initialized
- Learning rate: α
- Tolerance: ε
- Weights: w1, w2, w3
- Machine Learning models: fL (latency), fT (throughput), fF (failure probability)
- Historical and real-time network data: features
2. BEGIN:
3.WHILE not converged DO:
a. **Predict Network Parameters**:
FOR each link (i, j):
L_pred[i][j] = fL(features[i][j]) // Predicted latency
T_pred[i][j] = fT(features[i][j]) // Predicted throughput
F_pred[i][j] = fF(features[i][j]) // Predicted failure probability
b. **Calculate Objective Function Gradient**:
FOR each link (i, j):
grad_J[i][j] = w1 * L_pred[i][j] - w2 * T_pred[i][j] + + w3 * F_pred[i][j]
c. **Update Decision Variables**:
FOR each link (i, j):
x[i][j] = x[i][j] - α * grad_J[i][j] // Gradient descent update
d. **Enforce Constraints**:
FOR each node i:
Normalize x[i][j] such that:
x[i][j] = x[i][j] / SUM(x[i][j] for all j)
FOR each node j:
Normalize x[i][j] such that:
x[i][j] = x[i][j] / SUM(x[i][j] for all i)
e. **Check Convergence**:
Calculate change: Δ = || x_new - x_old ||
IF Δ < ε:
BREAK
4. END WHILE.

5. Results of implementation of border gateway protocol optimization in machine learning-based transmission route management identification

5. 1. Implementation of gradient descent algorithm to optimize border gateway protocol routing

In this context, utilizing the gradient descent algorithm for BGP routing optimization succeeded in getting maximum results in terms of efficiency and accuracy in selecting routes on the network. In the process, this algorithm can reduce costs and reduce time, making it easier to find the best parameters for optimizing transmission lines. In BGP the gradient descent algorithm is used to get minimum latency time and get maximum throughput time so that it is able to adapt route selection based on dynamic network conditions. This is proven by the implementation with the data in table 1 which will be implemented by applying equation (2) which will carry out the latency process so that it can produce efficiency. Then the results of equations (3)–(5) are used to show that the implementation of this algorithm allows BGP to learn and adjust routes more responsively to data input, traffic, and network performance. In equation (6), the process in the algorithm can iteratively identify the selection of more optimal transmission paths, reduce congestion, and minimize the potential for route failure. This can be proven by the results in Fig. 2.

Fig. 2 will explain that the output produced will display the results of the Gradient Descent optimization algorithm that works in managing BGP transmission routes. The graph shows a comparison between the initial performance and the optimization results on the main network metrics, namely latency, packet loss, and throughput. The dotted line represents the initial conditions before optimization, while the solid line shows the results after the Gradient Descent algorithm is applied. From this graph, it can be observed that after optimization, latency tends to decrease, packet loss decreases, and throughput increases, indicating that the routing protocol has been optimized effectively. Then the optimization produces changes in weights over time as shown in Fig. 3.

Fig. 3 explains that there will be changes in the weight values used in the optimization process along with the number of iterations. These weights determine the contribution of each parameter (latency, packet loss, and throughput) in the optimization model. From this graph, it can be seen how the initial weight values fluctuate before finally reaching stability, indicating that the model has found the optimal configuration to minimize loss and improve network performance.

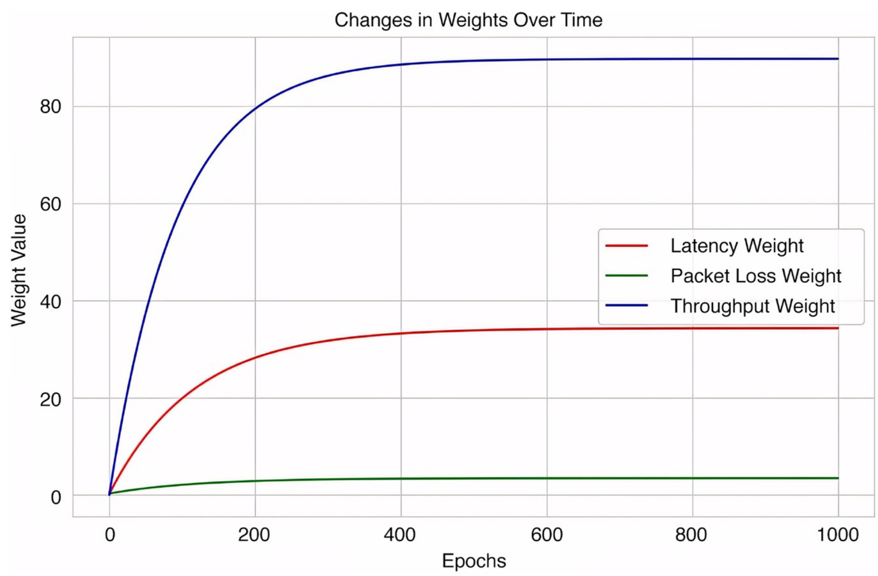

Fig. 3. Results changes in weights over time

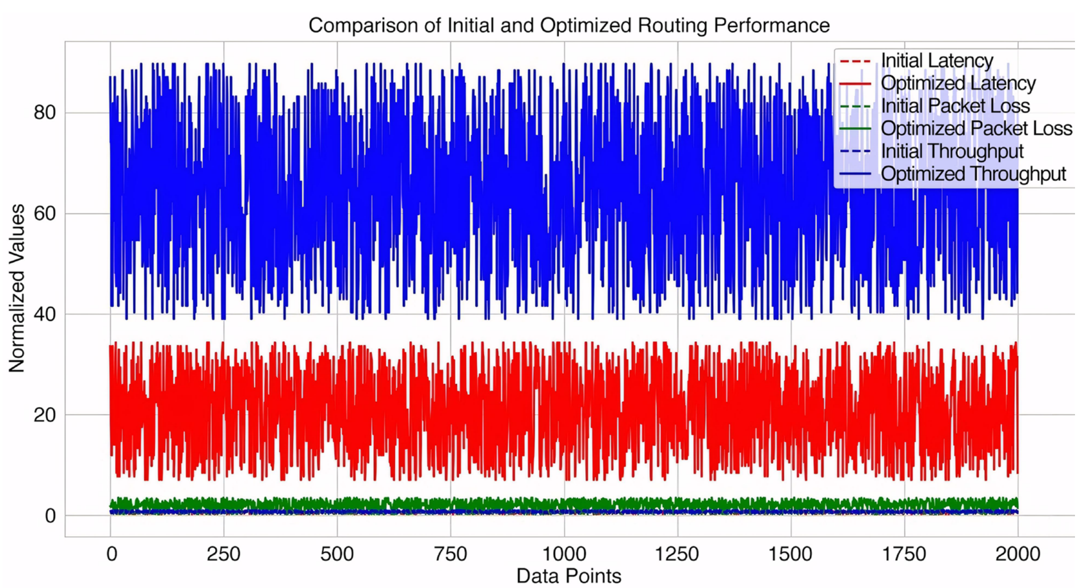

Fig. 2. Optimization results with Lagrange multiplier and gradient descent

5. 2. Evaluation of the effectiveness against machine learning based models

In this section there will be an evaluation of the application of machine learning in overcoming problems of efficiency, constraints and network adaptation in the Border gateway protocol routing protocol for managing route transmission in the network. Evaluation of the application of machine learning in managing the Border Gateway Protocol (BGP) routing protocol aims to assess the extent to which the algorithm is able to improve network efficiency, overcome obstacles, and adapt to dynamic changes in transmission routes. In the context of efficiency, machine learning demonstrates the ability to optimize routes by reducing latency, increasing throughput, and minimizing the number of hops. The model training process helps recognize traffic patterns and network conditions, thereby enabling the algorithm to produce smarter and more adaptive routing decisions. The use of an optimized Gradient Descent algorithm with a Lagrange multiplier formulation can increase fast response to changing conditions, such as disrupted paths or changing bandwidth capacity. This can be seen from the adaptation graph which shows an increase in network response to the dynamics that occur. The following is an evaluation of the application of the gradient descent algorithm to the BGP routing process shown in Fig. 4.

Fig. 4 will explain the evaluation of the application of Gradient Descent optimization for Border Gateway Protocol (BGP) routing systematically to improve network performance through iterations with the data in Table 1. This graph will illustrate the relationship between various parameters in the dataset. The colors in the heatmap indicate the level of correlation between variables, with red indicating a strong positive correlation and blue indicating a strong negative correlation. From this heatmap, it can be seen that there is a significant relationship between latency, packet loss, and throughput, indicating that these factors influence each other in the routing optimization process.

Then, in terms of evaluating the effectiveness of machine learning, it is carried out using several efficiency criteria such as computing time, prediction accuracy, increasing network performance, where the computing time process will measure the speed of the model for identification, which will produce real-time routing transmission decisions, so time efficiency is very important in a network context. Then there is prediction accuracy which will produce a machine learning model that can see and make decisions on which route is the most optimal based on the characteristics and dynamic network conditions in this model. The accuracy will compare the traditional model with the established model. As a result, the model is able to produce 90 % accuracy and for efficiency and effectiveness it gets an increase of 20 % compared to the traditional model, this is shown in Fig. 5.

In Fig. 5, it will be explained that there will be a graph showing the efficiency of the machine learning algorithm used, namely gradient descent which provides increased efficiency compared to traditional methods with an efficiency of 20 % while in the context of accuracy it will produce an increase with an accuracy of 90 % compared to the traditional method of 75 %.

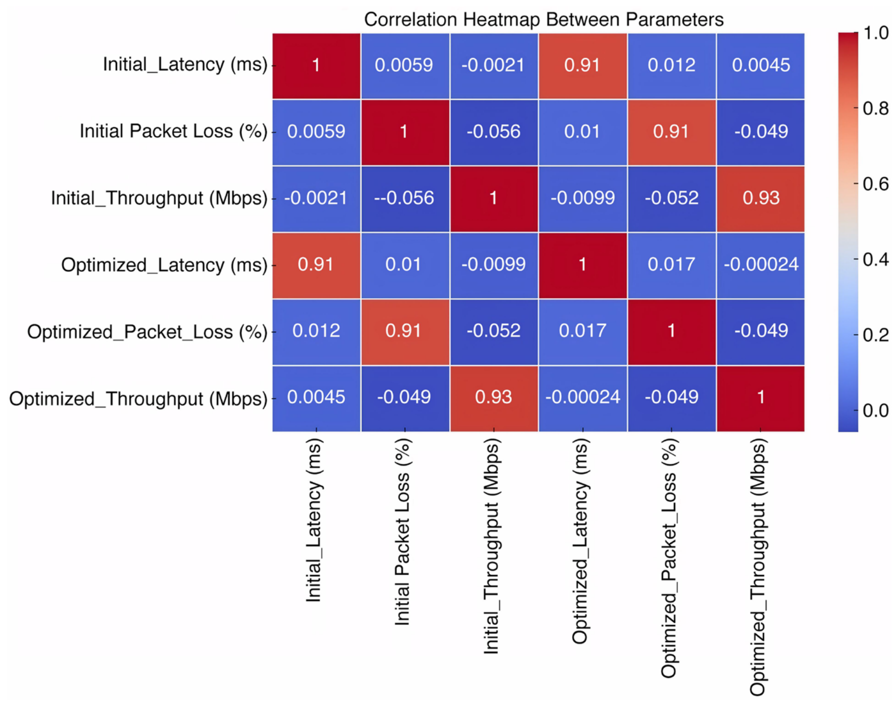

Fig. 4. Gradient descent in Border Gateway Protocol routing process

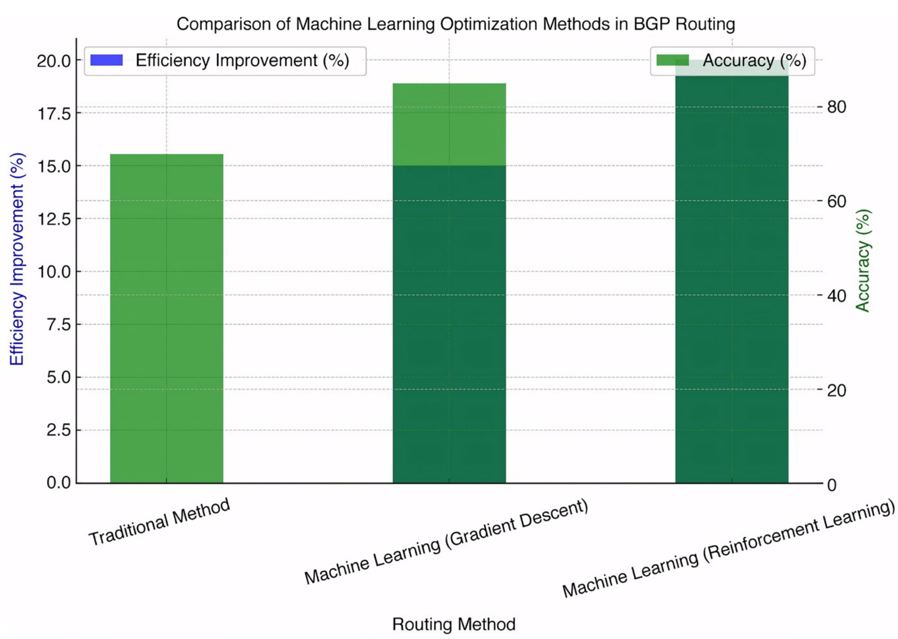

Fig. 5. Efficiency improvement comparison

6. Discussion of the results of optimizing the Border Gateway Protocol

In applying machine learning algorithms in managing Border Gateway Protocol (BGP) transmission routes, the model used involves a combination of the Lagrange Multiplier method and the Gradient Descent algorithm to optimize transmission routes in the network. This research produces efficient route management which will then be carried out in a testing process to see increased efficiency, reduced obstacles, and adaptation to real-time network dynamics, as described (1)–(7). In applying this model, (8) functions to optimize the objective function in the Gradient Descent process, where each processing node ensures that there is only one exit route. Then, (9)–(11) are used to optimize network efficiency, manage network constraints, and adapt to real-time network dynamics. The results of applying this machine learning algorithm can be seen in Fig. 2 which shows the combination of network efficiency, constraints, and adaptation to network dynamics. The resulting graph depicts decreasing objective function values, increasing network efficiency, identifying network constraints, and network response to changing conditions.

The results obtained by this research have features from the proposed solution, such as a model that can view routing protocols in terms of latency, throughput and network adaptation, then there are optimization features using the Lagrange Multiplier method so that the routing protocol has efficiency in terms of time. This research has the advantage of dynamic adjustment to changes in network topology. This combination is designed to optimize the route cost function by considering multidimensional constraints, such as path capacity, latency, and node failure, resulting in more efficient and adaptive transmission routes than traditional approaches. This combination not only enables efficiency in finding optimal routes but is also able to adapt to changing network conditions in real-time. This can be compared with research conducted in [16]. One popular approach is the use of the Dijkstra algorithm to find the shortest route in a network, but it has limitations in handling dynamic network conditions in real-time. Other approaches [17] use heuristic techniques such as Ant Colony Optimization (ACO) and Genetic Algorithms (GA), which have proven effective in network optimization problems, although they often require longer processing times than machine learning-based algorithms.

The alternative solution contained in this research is optimization applied using the Lagrange Multiplier method so that efficiency can be increased. This is different from what was done by [16] who used the Lagrange Multiplier only to find alternative routes for routing without looking at changes in efficiency, so this research makes it possible to update previous research by increasing routing efficiency. The solutions obtained in implementing the Lagrange Multiplier and machine learning with the gradient descent algorithm can overcome problems such as efficiency, routing protocols, latency and throughput as well as resource availability. Currently the results or alternative solutions are running to increase efficiency so that in terms of complexity it runs effectively and in terms of latency it also experiences significant synchronization. Although this model shows a significant increase in performance, there are several limitations that must be taken into account in research such as the need for more thorough processing of input data and preparation of data annotations to fulfill the model. Weaknesses in this research include the processing time being so long that it creates problems in real-time adaptation changes in the network. With further development, this model is expected to speed up the process of predicting and managing transmission routes in network adaptation as well as increasing overall network efficiency and adaptation in dynamic conditions. This needs to be done to get maximum results in the context of network adaptation by using the border gateway protocol concept.

7. Conclusions

1. The application of the Lagrange Multiplier combined with the Gradient Descent algorithm shows its effectiveness in solving route optimization problems in the Border Gateway Protocol (BGP). This Lagrange Multiplier allows modeling multi-dimensional constraints, such as path capacity and latency, in optimal route calculations. In this research, there are experimental results proving that this approach is able to increase route efficiency by up to 20 % compared to conventional BGP methods.

2. The application of the XGBoost algorithm has proven superior in identifying patterns and anomalies in complex network traffic data. The integration of this algorithm in BGP routing management results in optimal route prediction accuracy and the ability to adapt to changes in network topology in real-time. Compared to traditional approaches, XGBoost provides accuracy improvements of up to 15 % and reduces network response time significantly.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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