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Original Article

Two-Tier Intelligent Optimization Framework for Trust-Aware Clustering and Energy-Efficient Routing in VANET Communication

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Abstract *- Vehicular Ad hoc Network (VANET) is a currently developing trend that inspires the delivery of several service providers in urban regions. In VANETs, the vehicles signify the nodes in the Network, which want to assure superior assistance when there is a greater node density. In this framework, the combination of probable clustering techniques has the probability of enhancing the safety of the road and easing a trustworthy choice of encouraging message route. The clustering protocols were defined as the perfect candidate for resolving network scalability issues and ensuring reliable data propagation. This study proposes a Two-Tier Intelligent Optimization Framework for Trust-Aware Clustering and Energy-Efficient Routing (TTIO-TACEER) model in VANET. The main purpose of the TTIO-TACEER model is to integrate an optimized clustering mechanism with an efficient routing strategy to enhance network performance and reliability. In the clustering phase, the TTIO-TACEER technique is applied using the Goose Algorithm (GO) to select optimal Cluster Heads (CHs). Furthermore, the multi-criteria Fitness Function (FF) considers Residual Energy (RE), Trust Level (TL), Degree Difference (DD), Total Energy Consumed (TEC), and mobility for cluster formation. TTIO-TACEER is implemented using the Ninja Optimizer Algorithm (NiOA) to optimize routing paths between CHs and the Base Station (BS) in the routing phase. Moreover, the routing FF considers the distance to the BS to improve data transmission reliability while reducing latency (LAT). An extensive simulation validation is executed to highlight the significance of the TTIO-TACEER technique. A brief comparative study described the superior results of the TTIO-TACEER technique when compared to other existing models.*

Keywords *- VANET, Clustering, Goose Algorithm, Energy-efficient routing, Ninja Optimizer Algorithm, Fitness function.*

1. Introduction

VANET is an infrastructure-free and self-organizing connection utilized in vehicular settings to interact between roadside infrastructure, pedestrian personal devices, and automobiles. VANET is an essential domain of analysis that highlights accident prevention, information systems, and effective driving [1]. To guarantee the security of VANET, a larger number of numerical interactions are presently being built. Additionally, the existing situation, with the emergence of a road safety method, is essential. Owing to these connections, co-operative applications can analyze, acquire, and disseminate roadway traffic data. Persistent connection disruption among VANET nodes is initiated by excessive node mobility, coverage confines, and the presence of impediments [2]. In VANET, dual models of communication exist: Vehicle to Infrastructure (V2I) and Vehicle to Vehicle (V2V) communications. Either non- or safety messages are transferred through V2V communication, which is only capable of shorter-range vehicular systems. V2I communication is utilized in longer-range vehicular systems that depend on pre-communications frameworks like wireless access points [3]. Clustering is related to the process of separating the overall system into smaller logical types of vehicular nodes [4]. This clustering method is acquired depending upon the features of transmission link capability and inter-node distance to enhance the execution of the overall system. In addition, the clustering mechanism might be categorized based on the guidelines deliberate for cluster construction [5]. Nevertheless, a cluster network vehicular node might be selected as CH or serve as the Cluster Member (CM) [6]. CHs are crucial in accomplishing inter- and intra-clustering data forwarding methods, whereas CM nodes are ordinary nodes in VANET. Therefore, CH is always chosen based on attaining superior functionality features to enhance the performance of the Network [7]. The routing protocols in VANET are separated into 4 classes: cluster, topology, location, and broadcast-based routing protocols [7]. While sending node broadcasts the Route Request (ROREQ) packet to the neighbouring nodes, and it can upgrade the local routing table instantly after receiving it, subsequently forward the ROREQ to their neighbouring nodes, and repeat this procedure until the ROREQ is sent to the targeted node [9]. Because of the faster-moving vehicles on the road, the vehicular network topology modifies rapidly. The transmission routing protocol utilizes the flooding model for sending packets to each node in the system [10]. VANETs are substantial in enabling seamless communication among vehicles, pedestrians, and roadside units, thus facilitating safer and more efficient transportation systems. However, the highly dynamic nature of vehicular environments poses crucial threats to maintaining stable and secure communication. The overall network performance and data transmission quality may be degraded by the network topology discrepancies and frequent disconnections. There is also a requirement for intelligent mechanisms that can adapt to these threats, ensuring reliable data exchange while optimizing resource usage. Addressing these issues is significant for improving road safety, traffic management, and real-time decision-making in smart transportation systems.

This study proposes a Two-Tier Intelligent Optimization Framework for Trust-Aware Clustering and Energy-Efficient Routing (TTIO-TACEER) model in VANET. The main purpose of the TTIO-TACEER model is to integrate an optimized clustering mechanism with an efficient routing strategy to enhance network performance and reliability. The major contribution of the TTIO-TACEER model is listed below.

- The GO is utilized for effective CH selection in the clustering phase based on multiple criteria. It improves energy efficiency, balances load distribution, and extends network lifetime. The adaptive and intelligent cluster formation also assists in dynamic environments. This enhances the overall network performance and ensures reliable data aggregation.
- A multi-criteria FF is utilized in the clustering phase that considers RE, TL, DD, TEC, and NM. This model ensures the selection of stable, energy-efficient, and trustworthy CHs, and clustering accuracy is improved. The model adapts to dynamic network conditions and also enhances network reliability, energy balance, and secure data transmission.
- The NiOA model is integrated in the routing phase to determine the optimal paths between CH and BS dynamically. This approach minimizes routing overhead and improves end-to-end data delivery efficiency. It also assists in adaptive path selection under diverse network settings and improves throughput and reliable communication, while mitigating energy utilization.
- The distance to the BS is incorporated by the routing FF for prioritizing the routes that reduce latency and improve data transmission reliability. This model also enhances real-time communication and mitigates network delays. It adapts routing decisions and assists efficient, low-latency data delivery while maintaining energy efficiency.
- A novel dual-phase optimization framework integrating GO and NiOA models. The incorporation of two nature-inspired algorithms synergistically enhances energy efficiency and communication reliability. This novel integration addresses both clustering and routing threats. It represents a crucial improvement in optimizing performance through hybrid bio-inspired techniques.

2. Related Works

Rajeswari and Kousalya [11] developed an IEMOC technique. This model utilizes an intellectual Bezier route selection model for handling difficulties hindering the way of the FANET node. Suppose a link failure arises owing to a difficulty in the system. In that case, the proposed protocol chooses an optimum alternate routing path through neighbouring nodes depending upon its link duration, mobility awareness aspect, route availability, system connectivity, and improving the failed router without originating the method of route discovery. Choksi and Shah [12] developed energy-aware and distance clustering models called SOMNNDP that employ a SOMNN-based ML model to execute faster multi-hop data dissemination. Residual node energy and Individual Euclidean distances are deliberated as mobility parameters across the cluster routing method. It increases VANET lifetime by confirming that each transitional vehicle node utilises energy at a similar rate.

In [13], the succeeding stages are comprised of the advanced Fuzzy-Topsis (FT) and Energy-Efficient Cluster-Based Routing (EECR) in VANET: CH selection, fault tolerance, and routing. Primarily, the Hybrid Shuffled Shepherd Namib Beetle Optimizer Algorithm (HSS-NBO) methodology that is focused on the preceding work is utilized to pick the CH. Subsequently, employing the created Combined Jellyfish Beluga Whale Optimizer (CJ-BWO) method, routing is done as effectively as possible while taking into account factors like quality of service, energy, delay, trust, security, and connection quality (RSSI).

Thus, a prerequisite for energy-effective processing, the intermediate node forwarding mechanism is implemented for void handling. Sajithabegam and Menakadevi [14] projected improvement to dynamic adaptive cluster-based routing to reduce sub-optimal decisions in VANET. EDBC employs distance and energy metrics among cluster centres, vehicles, or Roadside Units (RSU). A fitness model recognizes that CH depends upon the nodes with maximum fitness values. The consequent CH, selected for its stability, dynamism, and energy efficacy, is obtained by integrating the LBFCM with the fitness model. Darabkh et al. [15] developed an intellectual routing protocol that presents an innovative clustering model for choosing CH. This selection model improves route stability, decreases longer-range communication, and considerably lowers control overhead. In previous study, an innovative SGO-EACA model is presented. In addition, the projected model originates from FF and comprises several metrics. In [16], a novel routing protocol is presented. This protocol aims to improve the route selection method by using several metrics, such as node density and node mobility speed. Accordingly, this model presents a novel FF as the optimizer base for the GA.

Kanimozhi and Sara [17] improved the energy efficiency and prolonged the lifetime of Wireless Sensor Network (WSN)-based Internet of Things (IoT) by utilizing an improved clustering protocol. This model utilizes the Modified Fuzzy C Means (MFCM) approach for stable clustering and the Modified Glowworm Swarm Optimization (MGSO) technique for balanced CH selection. Alotaibi et al. [18] improved routing efficiency and communication reliability in VANETs by using the Falcon Optimization Algorithm-based Energy Efficient Communication Protocol for Cluster-based Routing (FOA-EECPCR) technique for vehicle clustering and the Sparrow Search Algorithm (SSA) approach for optimal route selection. Shukla and Sawarkar [19] improved energy efficiency and throughput in 5G heterogeneous networks by introducing the Dynamic Resources Optimisation and Interference Management-based Green Communication Protocol (DROIM-GCP) methodology by using type-2 fuzzy logic for optimal user equipment selection and handover management.

Alotaibi et al. [20] developed a robust anomaly detection system by using an Improved Whale Optimization Algorithm-based Feature Selection with Explainable Artificial Intelligence (IWOAFS-XAIAD) model by incorporating CNN with Bidirectional Long Short-Term Memory (CNN-BiLSTM) with attention and Catch-Fish Optimization Algorithm (CFOA) models for hyperparameter tuning to improve detection accuracy and interpretability. Tong and Weng [21] developed an intelligent routing algorithm for Software-Defined Networking (SDN) by employing fuzzy set control and neural network-based reinforcement learning for optimizing routing decisions and network security.

Dongare, Jondhale, and Agarkar [22] proposed an energy-efficient node selection method based on trust level, connectivity degree, and distance to the sink, improving performance over protocols like Shortest Hop Routing (SHORT), Power Efficient Gathering in Sensor Information Systems (PEGASIS), Optimized Reduced Energy Consumption (OREC), and Load Balance and Energy Efficient Routing Algorithm (LBEERA). UmaRani et al. [23] proposed a model to improve energy efficiency and extend the lifetime of WSNs by using a hybrid Ant Colony Optimization (ACO) and Improved Social Spider Cluster Optimization Algorithm (ISSOA) models for optimal CH selection, along with an Optics-Inspired Optimization (OIO) approach for efficient routing. Thanedar and Panda [24] aimed to mitigate Energy Consumption (EC) in Fog Nodes (FNs) by proposing an Energy-Efficient Resource Allocation (EERA) approach that optimizes resource block allocation among FNs to improve service delivery and energy efficiency.

The existing models show significant enhancements but exhibit limitations in various areas. For instance, they lack adaptability to dynamic network conditions and insufficient security threat handling. Furthermore, the trade-offs between energy efficiency, latency, and reliability are not considered properly, and various techniques focus on single-objective optimization. Moreover, various models depend on static clustering or routing strategies, which may not perform well in highly mobile or large-scale networks. The integration of explainability in AI-based models remains restricted, affecting trust and transparency. There is also a research gap in addressing scalable and real-time decision-making in diverse network environments. Improving multi-metric optimization with low overhead and enhanced robustness remains a critical challenge.

3. Materials and Methods

In this study, the TTIO-TACEER model in VANET is proposed. The main purpose of the TTIO-TACEER model is to integrate an optimized clustering mechanism with an efficient routing strategy to enhance network performance and reliability. Figure 1 demonstrates the workflow of the TTIO-TACEER approach.

3.1. Cluster Formation: GO

In the clustering phase, the TTIO-TACEER technique is applied using the GO to select optimal CHs [25]. This model is chosen for its robust searching capability. The model assists in avoiding local optima while also effectually balancing the exploration-exploitation phases. This model also illustrates faster convergence and better adaptability in dynamic network environments compared to conventional models such as PSO or GA.

The model also facilitates resource-constrained WSNs due to its simplicity and fewer control parameters. This technique is also computationally efficient and shows excellence in handling multi-objective optimization with the complex criteria involved in CH selection, thus resulting in enhanced energy efficiency and network stability. The GOOSE technique is a heuristic optimizer model, which is dependent upon a greedy strategy, intended to tackle the false extrema task in higher-dimensional and intricate issue domains. By gradually enhancing the solution excellence in local search spaces, the method efficiently alleviates the danger of becoming stuck in a sub-optimal solution. The GOOSE technique is mainly suitable for optimizer tasks, which are categorized by the occurrence of many local goals or complex nonlinear relationships throughout the procedure. The GOOSE technique rests on its iterative search of the solution spaces, using a local greedy tactic to reduce the hazard of meeting local extrema. In every iteration, the technique picks an optimum solution depending on the neighborhood data of the present solution and directs the exploration procedure using a heuristic rule, thus improving the solution quality gradually.

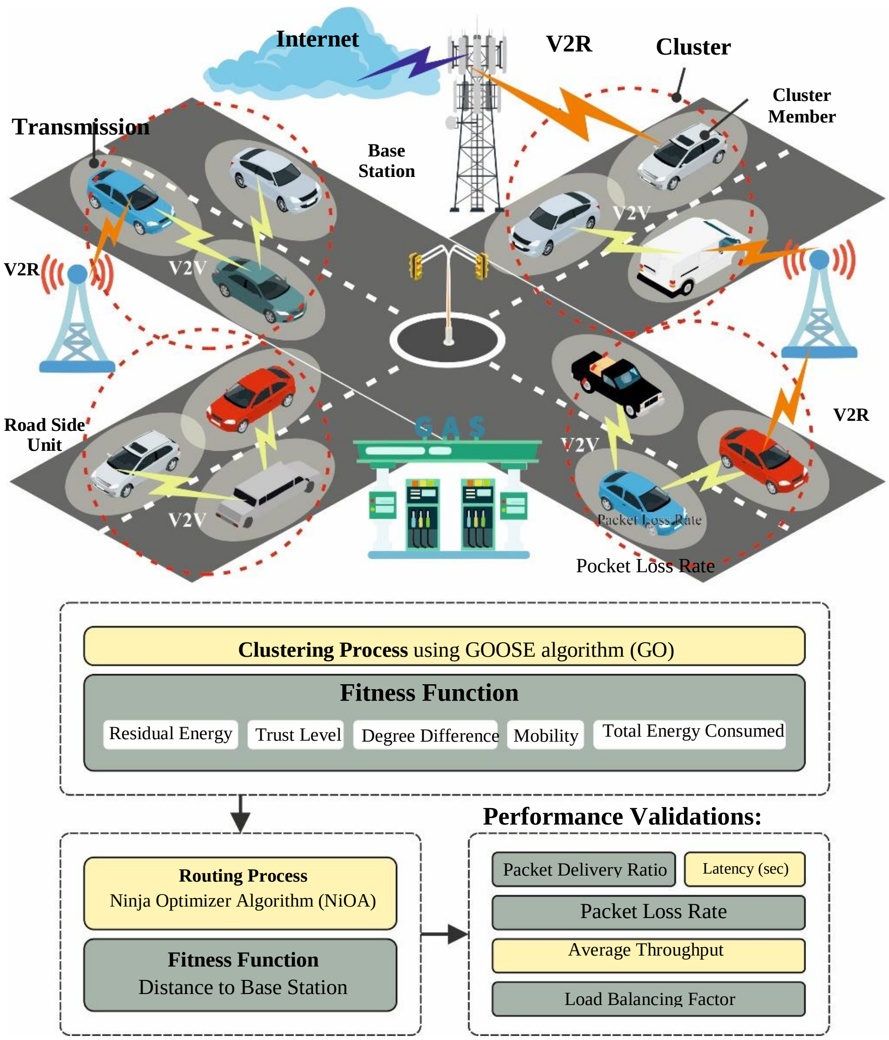


Fig. 1 Workflow of the TTIO-TACEER method

The vital stages of the GOOSE technique contain setting the population, picking the finest solution, assessing fitness, performing local exploration, upgrading the set of solutions, and defining whether the termination conditions are converged. Particularly, an early set of solutions is produced at random in the space of solutions. The essential computation of the GOOSE model mainly includes the solution upgrade mechanism, FF, and neighborhood exploration tactic.

If an optimizer issue is defined by the objective function $f(x)$, while $x = (x_1, x_2, \dots, x_n)$ signifies the solution space of an issue. The main intention is to enhance $f(x)$ for identifying an optimum solution. The mathematical formulation is given below:

$$f(x) = \sum_{i=1}^{n} w_i \cdot x_i^2, \quad (1)$$

While, w_j denotes a weight, and x_i Means the value of ith module. The strategy of greed is established on the region solutions surrounding the present solution, and it repeatedly hunts the space of solutions as per the following upgrade formulation:

$$x^{new} = x + \Delta x \quad (2)$$

Here, Δx signifies the optimum change in the present solution in its district, normally calculated utilizing a heuristic. Depending upon this, the technique assesses the fitness of every upgraded resolution and picks the best one for the subsequent iteration. The benefit of the GOOSE technique rests in its usage of a greedy strategy that efficiently averts the danger of being stuck in local goals owing to randomly generated exploration and also permits the classification of an approximate global optimum in higher-dimensional solution spaces. However, the neighborhood search tactic and early solution have an impression on the performance of the model. Therefore, optimizer and tuning are needed for real-world applications, which depend upon the exact issue.

3.2. FF: Cluster Protocol

Next, the multi-criteria FF considers RE, TL, DD, TEC, and mobility for cluster formation. This methodology ensures the selection of CHs that are not only energy-efficient but also reliable and stable in dynamic network conditions. This results in balanced consumption, prolonged network lifetime, and improved overall performance compared to single-metric methods. This model also improves security and adaptability, and mitigates cluster instability and communication.

3.2.1. RE of Node

The RE of the nodes is set in Equation (3), which computes the RE by subtracting the energy consumed during network operations from the initial energy allocated to each node. This value is significant for determining the ability of the node to participate in communication tasks such as data transmission or CH selection. Monitoring RE assists in balancing EC across the Network, thereby extending its overall lifetime and improving efficiency.

$$RES\ energy = Initial\ energy - consumed\ energy \tag{3}$$

3.2.2. TL Value

At the start, the trust value is similar to that of every node. The anomaly recognition technique lessens this level if the node is imperfectly functioning. There is a probability of an abnormal node, which might become a distrusted or malicious node.

$$Normal\_Sensor\_node: 0.7 \leq Ti \leq 1$$

$$Distrusted\_Sensor\_node: 0.3 \leq Ti \leq 0.7$$

$$Malicious\_Sensor\_node: 1 \leq Ti < 0.3$$

For a CH, only a normal node is permissible to donate. It is probable for the node to be malicious at any point, and so $Distrusted\_Sensor\_$ node and $Malicious_Sensor_$the node might not contribute to the assortment of CH. If the RE of the normal node is smaller than the RE of the average of every node, then it is named a malicious node.

3.2.3. DD

The constancy of node as a CH upsurges with the Node Degree (ND). The ND denotes the connection number, which has other nodes in the Network. Di represents the ith nodes of practical degree and Max_D refers to a maximum degree, signifying the DD D_D as $|Di - \mathrm{Max}_D|$. If the D_D If the value is small, then the node I achieves the optimum as CH.

3.2.4. TEC

The RE of node ni as signified by Eri after Conveying k bits to the node nj in the distance d is presented and computed below.

$$Eri\ = E - (ETx(k,d) + ERx\_elec(k)) \tag{4}$$

While E denotes the current energy of the node E_{Tx} signifies the energy for conveying the message as given below.

$$ETx(k,d) = kEelec\ + K\ Eampd2 \tag{5}$$

Here, $Eelec$ means the electron energy, and $Eamp$ denotes an amplified energy. $ERx - elec$ is said to be consumed energy for receiving the message.

$$ERx\_elec(K) = kEelec \tag{6}$$

3.3. Mobility of Node

Mobility is a vital factor to be measured while selecting the CH. Let's pick a more stationary CH that will be more predictable. Re-affiliation may take place if the CH quickly transfers, which causes nodes to become detached from each other. This occurs once the node leaves the current cluster and joins a novel one. In such a state, a lesser quantity of data is conveyed between the CH and the nodes, so the node's mobility is employed as a dividing factor.

$$Mi\ = \frac{1}{T}\sum_{t=1}^{T}\sqrt{(Xt - Xt - 1)^2 + (Yt - Yt - 1) + (Zt - Zt - 1)} \tag{7}$$

The node weight W_i It is computed by Equation (8) for every node to participate in the CH selection:

$$W_i = (w1 \times T_i + w2 \times \mathrm{Res}_i + w3 \times D_i + w4 \times Total\ Eng_i + w5 \times Dist_i) / Mobility\ of\ a\ node(M_i) \tag{8}$$

In Equation (8), $w1$, $2, w3$, $w4$, and $w5$ specify the coefficients.

3.4. Routing Formation: NiOA

In the routing phase, TTIO-TACEER is implemented using the concept of the NiOA, which is employed to optimize routing paths between CHs and BS [26]. In the routing phase, the routing paths are optimized between CHs and BS. The model is also effective for its robust global searching capability and fast convergence. This technique also efficiently balances exploration and exploitation, thus enabling the exploration of energy-efficient and reliable routes in dynamic network conditions. This methodology adapts well to altering topologies and reduces latency and EC, compared to conventional routing algorithms. The nature-inspired approach also facilitates flexible multi-objective optimization, thus enhancing the overall network performance and data transmission reliability. Figure 2 represents the flowchart of NiOA.

NiOA works by altering the system parameter in a beneficial way, which will develop the searching space, evade local goals, and move near global goals. The main elements of NiOA were recognized by the shift of agents, their connections with additional agents, locations in previous times, external random values, and arithmetic functions such as the exponential function and cosine wave. NiOA trusts a control parameter set to adjust the exploitation and exploration procedures.

The parameter a is a randomly generated number between 6 and 10, as well as factors such as v_1, r_2, r_3, J_1, J_2, and n in a defined range for influencing the diverse features of the optimizer. For instance, r_2 and r_3 are random search movements, while J_1 and J_2 They are highly answerable for fine-tuning the stage of exploitation. The selection of these parameters delivers essential flexibility and signifies that NiOA is highly beneficial for an extensive range of optimizer tasks.

Fig. 2 Flowchart of NiOA

3.4.1. Exploration Phase

In this stage, the position of the agent L_s It is upgraded depending upon the present and previous locations, besides with randomly generated features that force the exploration, as exposed in Equation (9). The location upgrade formulation integrates a random factor. r_1, which permits the technique to discover novel areas of the searching space by computing the dissimilarity between dual locations at dissimilar times, t_1 and t_2. If the condition is not converged, the technique presents arbitrariness by picking a novel position from a predetermined one, permitting the search procedure to endure widely. It guarantees that the search shields an extensive collection of latent solutions, raising the probability of discovering the global optimal.

$$L_s(t+1) = \{L_s(t) + r_1 \cdot (L_s(t_1) - L_s\ , otherwise\ Random\ L_s(t)\ and \in F_S \qquad (9)$$

Here, F_S signifies the solution of fitness, which ensures an agent discovers novel locations efficiently.

The location of another agent D_s Is upgraded over a calculation that presents periodic variations utilizing a function of a cosine wave, in addition to a random factor r_2. This endurance permits the preservation of adaptability with γ, by evading cases where the hunt is stuck in local goals. The cosine wave transports the cyclic behavior that permits the technique to move to novel areas in a controlled manner.

$$D_s(t+1) = D_s(t) + |D_s(t)| + r_2 \cdot D_s(t) \cdot cos(2\pi t) \qquad (10)$$

The search procedure additionally incorporates the upgraded positions of D_s and L_s, which enables a complex search method, as defined in Equation (11):

$$S(t+1) = r_1 \cdot L_s(t+1) + r_2 \cdot D_s(t+1) \qquad (11)$$

3.4.2. Exploitation Phase

Here, the main attention moves from searching for refining the solutions that had previously been found. The technique utilizes a non-linear calculation including parameters. J_1 and J_2 controls an amount of exploitation, leading to step-by-step developments in the location of the agent. This stage is perfect for refining the solution found in the exploration stage, assuming that the technique fine-tunes an outcome at this phase.

The calculation of exploitation presents non-linearity, which leads to the optimization for discovering the local goals in the search space, owing to fewer incremental stages. The finest solution is measured by a non-linear calculation, which is exposed in Equation (12):

$$M_s(t+1) = J_1 \cdot M_s(t) + 2 \cdot J_2 \cdot \left(M_s(t) + (M_s(t) + J_1)\right) \cdot \left(1 - \frac{M_s(t)}{M_s(t)+J_1}\right)^2 \qquad (12)$$

NiOA integrates a reward or resource upgrade device to additionally improve an optimizer procedure. This upgrade is dependent upon an exponential development model, which is affected by a function of cosine, presenting periodic development in the reward state or resource. This periodic result certifies that the optimizer procedure stays adaptive and can react to altering conditions throughout the exploration. The usage of J_2 denotes a control parameter, which permits fine-tuning the reward upgrades, including one more layer of accuracy to a model, as signified in Equation (13):

$$R_s(t+1) = R_s(t) + (1 + R_s(t) + J_2) \cdot exp\big(cos(2\pi)\big) \quad (13)$$

If the finest solution is not altered for numerous iterations, the NiOA uses an upgrade calculation with the difference among the positions of agents. D_s and L_s, and the aid from R_s and M_s. The scaling factors i and n with an impact of parameter, include flexibility to this modernized device, permitting the technique to alter its method depending upon the present state of the optimizer procedure. The upgraded search near the solution unites the sophisticated values of M_s and R_s For improved exploitation, as specified in Equation (14):

$$S(t+1) = J_1 \cdot M_s(t+1) + J_2 \cdot R_s(t+1) \quad (14)$$

Over a mixture of fixed oscillations and random walks, non-linear variations, and reward-based changes, the NiOA averts the model from being stuck and aids it in coping with an obviously separated searching space.

3.4.3. Mutation

In NiOA, the mutation tactic is provided to insert a larger level of change into the procedure. This involves a summation calculation where signs alter to create a kind of non-linear mutation to the agent’s gesture. Obviously, the mutation parameter is acquired at random while its symbol is protected, thus the scale of built changes in dual iterations is dissimilar. This tactic evades the danger of creating an optimizer that is too deterministic and provides the method an opportunity to halt free from local goals and possibly discover more areas of the searching space. Therefore, if the solution does not enhance, a mutation tactic presents assortment by adapting the present solution depending upon manifold features.

$$s(t+1) = L_s(t+1) + i \cdot n \cdot \big(L_s(t+1) - D_s(t+1)\big) \cdot \big(M_s(t+1) + 2 \cdot r_1 \cdot R_s(t+1)\big) \quad (15)$$

Lastly, the parameters leading the exploitation and exploration stages guarantee the model’s efficacy and adaptability as defined in Equation (16).

$$r_1 \in [0,1], r_2 \in [0,1], J_1 \in [0,2], J_2 \in [0,2], i \in [0,1], n \in [0,2] \quad (16)$$

3.5. FF: Routing Protocol

Moreover, the routing FF considers the distance to the BS to improve data transmission reliability while reducing LAT [27]. The FF is carefully constructed to reduce latency and improve data transmission reliability. The optimal path selection is ensured by integrating diverse criteria, thus balancing EC and communication delay. This approach outperforms conventional single-metric routing metrics by adapting to network dynamics and traffic variations. Hence, it improves overall network efficiency, reduces packet loss, and supports timely data delivery in WSNs. After getting the demanded message, the source must pick the subsequent node to convey the packet. Node selection depends upon the fitness value, which covers the lifetime of the system. The NiOA model is employed to compute the nodes' fitness and pick the fit node. The fitness value is computed based on the node's distance to the BS.

$$Fitness = dist(i,j) + dist(j,bs) \quad (17)$$

The distance between dual nodes to the BS is computed utilizing the below mentioned formulation:

$$dist(i,j) = \sqrt{(x1-x)^2 + (y1-y)^2}$$

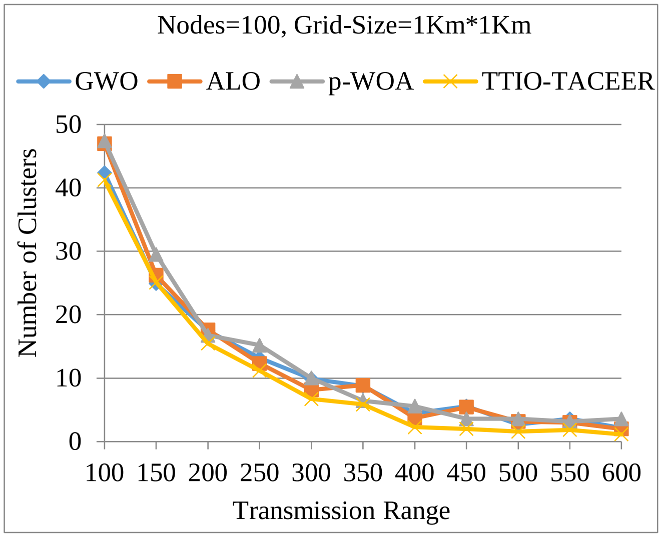
While i and j denote the parent nodes, bs represents the BS.

4. Result Analysis and Discussion

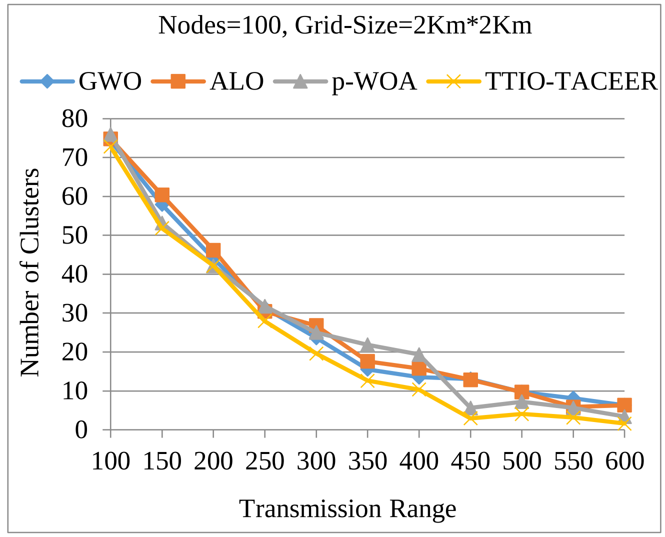
The performance evaluation of the TTIO-TACEER model is given with distinct measures. Number of vehicles (particles) (100), Epoch (350), Vehicle Speed (22-30 m/s), Grid size (area of Network) (1 km * 1 km to 4 km*4 km), Communication Range (100-600 m), Mobility Model (Freeway Mobility Model), Number of Simulations (10), Weights (0.5), Convergence Factor (0.001), Processor (AMD RadeonTM RX 5700 XT), Memory (8GB). The method is implemented in Python 3.6.5 and trained on an i5-8600k CPU with 4GB GPU, 16GB RAM, using a 0.01 learning rate, ReLU activation, 50 epochs, 0.5 dropout, and a batch size of 5. Table 1 and Figure 3 depict the overall Number Of Clusters (NOC) analysis of the TTIO-TACEER method with existing models under various distinct grid sizes (GS) and Transmission Range (TR) [28]. The result values state that the TTIO-TACEER approach has outperformed effective performances. With 100 nodes, GS is 1Km*1Km, and 100 TR, the TTIO-TACEER model gains a lower NOC value of 41.26, while GWO, ALO, and p-WOA models have attained higher NOC values of 42.40, 46.99, and 47.42. Afterwards, using 100 nodes, GS is 2Km*2Km, and 100 TR, the TTIO-TACEER technique reached a minimal NOC value of 72.80 while GWO, ALO, and p-WOA methodologies obtained improved NOC values of 74.37, 74.83, and 75.95. Meanwhile, using 100 nodes, GS is 3Km*3Km, and 100 TR, the TTIO-TACEER approach attains a decreased NOC value of 78.99, whereas GWO, ALO, and p-WOA methodologies have reached enhanced NOC values of 82.20, 95.80, and 90.36. Finally, using 100 nodes, GS is 4Km*4Km, and 100 TR, the TTIO-TACEER approach obtained a lower NOC value of 90.81, while GWO, ALO, and p-WOA techniques have accomplished superior NOC values of 93.50, 94.84, and 96.86.

Table 1. Comparative outcome of the TTIO-TACEER approach with other models under various GS

Nodes=100, Grid-Size=1Km*1Km				
Transmission Range	**GWO**	**ALO**	**p-WOA**	**TTIO-TACEER**
100	42.40	46.99	47.42	41.26
150	24.92	26.21	29.51	25.09
200	17.47	17.61	16.75	15.47
250	13.17	12.31	15.18	11.17
300	9.88	8.16	10.02	6.72
350	8.73	8.87	6.44	5.86
400	4.43	3.72	5.58	2.28
450	5.58	5.43	3.57	2.00
500	2.71	3.14	3.57	1.57
550	3.57	3.00	3.14	1.85
600	2.14	2.00	3.57	1.14
Nodes=100, Grid-Size=2Km*2Km				
100	74.37	74.83	75.95	72.80
150	57.92	60.40	53.19	51.84
200	43.95	46.20	42.14	42.14
250	31.32	30.42	31.78	27.94
300	23.66	26.82	25.01	19.60
350	15.55	17.58	21.86	12.62
400	13.52	15.77	19.38	10.36
450	13.07	12.84	5.63	2.93
500	9.69	9.69	7.21	4.05
550	8.11	5.86	5.63	3.15
600	6.31	6.31	3.38	1.57
Nodes=100, Grid-Size=3Km*3Km				
100	82.20	95.80	90.36	78.99
150	76.52	82.94	72.31	70.58
200	65.89	65.89	60.70	59.71
250	47.35	52.04	51.55	45.37
300	48.83	41.17	43.64	38.69
350	37.95	38.69	36.22	33.50
400	25.84	26.33	30.29	24.85
450	22.38	26.09	24.36	18.18
500	19.16	22.87	22.13	15.21
550	14.96	19.91	17.19	12.24
600	13.97	16.45	15.70	12.49
Nodes=100, Grid-Size=4Km*4Km				
100	93.50	94.84	96.86	90.81
150	89.02	89.02	93.72	81.18
200	73.79	78.04	82.75	71.55
250	68.86	66.62	71.99	59.67
300	61.91	62.14	61.47	55.64
350	46.90	46.01	48.47	42.46
400	44.22	40.41	44.22	38.63
450	33.69	35.93	37.05	32.27
500	30.78	31.00	32.12	27.78
550	28.31	27.42	30.10	25.85
600	26.52	23.61	26.97	21.26



(a)



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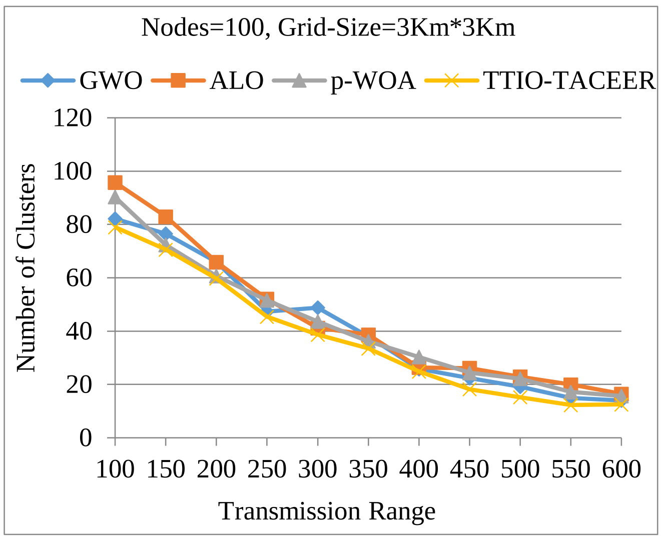

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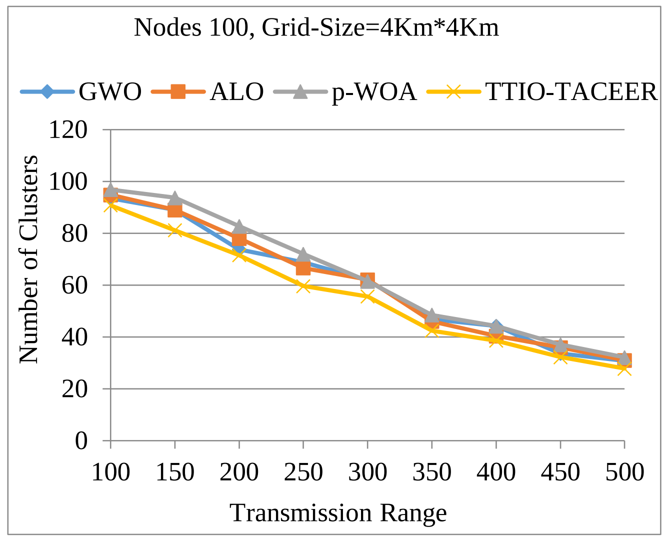

(d)

Fig. 3 Comparative outcome of TTIO-TACEER approach: (a) GS is 1Km*1Km, (b) GS is 2Km*2Km, (c) GS is 3Km*3Km, and (d) GS is 4Km*4Km.

In Table 2 and Figure 4, the performances of the TTIO-TACEER method are related in terms of packet delivery ratio (PDR). The values of the table showcased that the ALO and GWO techniques exhibited poor performance with minimum PDR.

Moreover, the p-WOA technique has gained judiciously closer PDR values. Nevertheless, the TTIO-TACEER model highlights its supremacy with a superior PDR of 92.22%, 79.10%, 60.66%, 54.92%, 45.49%, 34.84%, 24.59%, and 25.41% below vehicles 30-100 correspondingly.

Table 2. PDR outcome of the TTIO-TACEER approach with existing models under various vehicles

PDR (%)				
No. of Vehicles	**TTIO-TACEER**	**p-WOA**	**GWO**	**ALO**
30	92.22	90.17	80.33	74.60
40	79.10	74.19	60.66	44.26
50	60.66	54.92	54.10	40.57
60	54.92	57.79	50.00	35.66
70	45.49	49.59	29.10	30.74
80	34.84	39.75	20.49	25.00
90	24.59	29.10	15.16	20.49
100	25.41	19.26	15.16	18.03

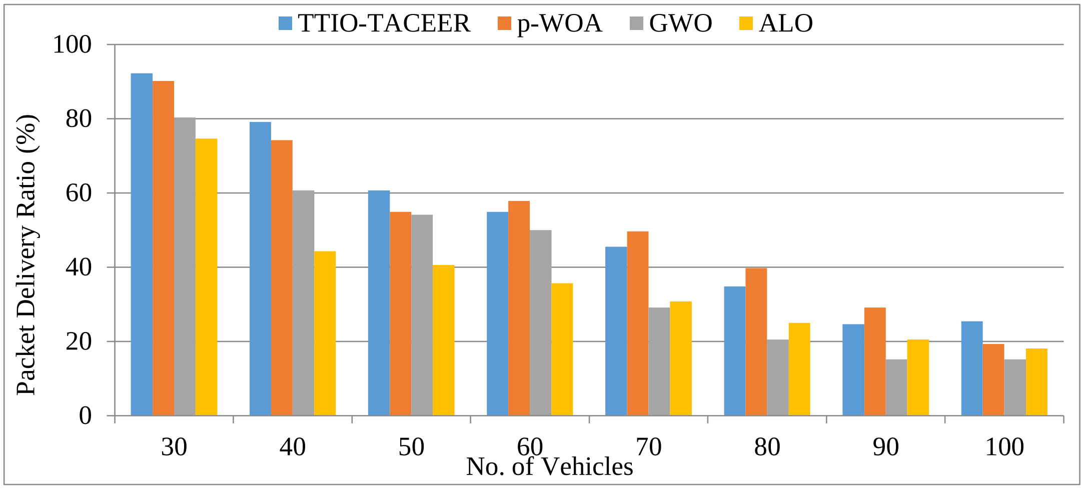

Fig. 4 PDR outcome of the TTIO-TACEER approach under various vehicles

Table 3 and Figure 5 imply the Packet Loss Ratio (PLR) outcomes of the TTIO-TACEER approach with existing methodologies. The outcomes inferred that the TTIO-TACEER approach realizes greater performance with lesser PLR values. With 30 and 100 vehicles, the TTIO-TACEER method attained a lower PLR of 7.78 and 74.59, but the p-WOA, GWO, and ALO approaches obtained a higher PLR of 9.83, 19.67, and 25.40; followed by 80.74, 84.84, and 81.97, respectively.

Table 4 and Figure 6 indicate the LAT results of the TTIO-TACEER approach with existing models. The performances inferred that the TTIO-TACEER method recognizes better solutions with minimum LAT values. Using 30 and 100 nodes, the TTIO-TACEER technique attains diminished LAT of 4.44s and 19.59s, but the p-WOA, GWO, and ALO models attained enhanced LAT of 9.79s, 29.99s, and 23.75s; followed by 30.29s, 67.71s, and 78.11s, correspondingly.

Table 3. PLR outcome of the TTIO-TACEER approach with existing models under various vehicles

PLR				
No. of Vehicles	**TTIO-TACEER**	**p-WOA**	**GWO**	**ALO**
30	7.78	9.83	19.67	25.40
40	20.90	25.81	39.34	55.74
50	39.34	45.08	45.90	59.43
60	45.08	42.21	50.00	64.34
70	54.51	50.41	70.90	69.26
80	65.16	60.25	79.51	75.00
90	75.41	70.90	84.84	79.51
100	74.59	80.74	84.84	81.97

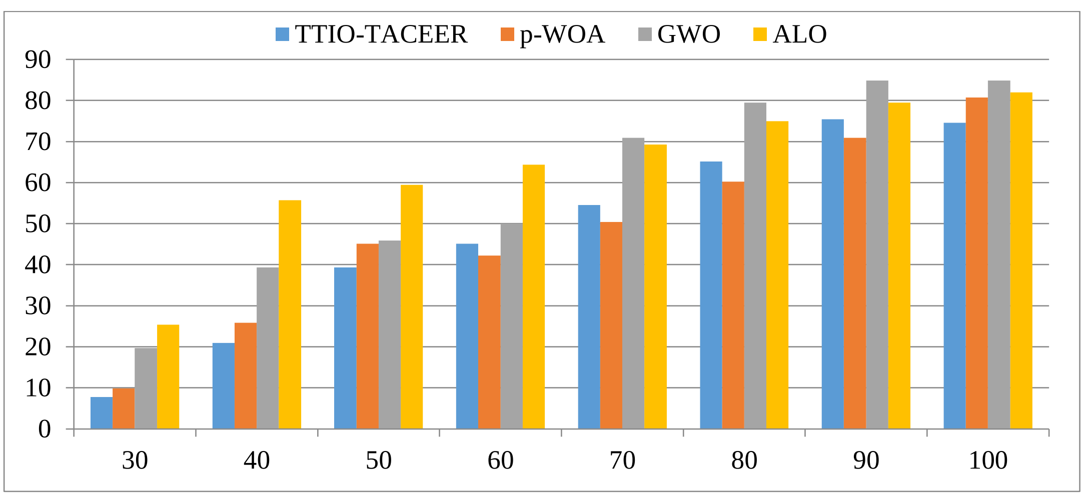

Fig. 5 PLR outcome of the TTIO-TACEER approach under various vehicles

Table 4. LAT outcome of the TTIO-TACEER approach with existing models under various nodes

LAT (sec)				
Number of Nodes	**TTIO-TACEER**	**p-WOA**	**GWO**	**ALO**
30	4.44	9.79	29.99	23.75
40	4.44	8.31	34.15	38.30
50	7.12	14.25	34.15	38.60
60	10.38	19.89	38.30	47.22
70	10.68	20.48	49.29	52.86
80	10.68	19.30	48.40	57.31
90	21.08	29.39	57.91	67.12
100	19.59	30.29	67.71	78.11

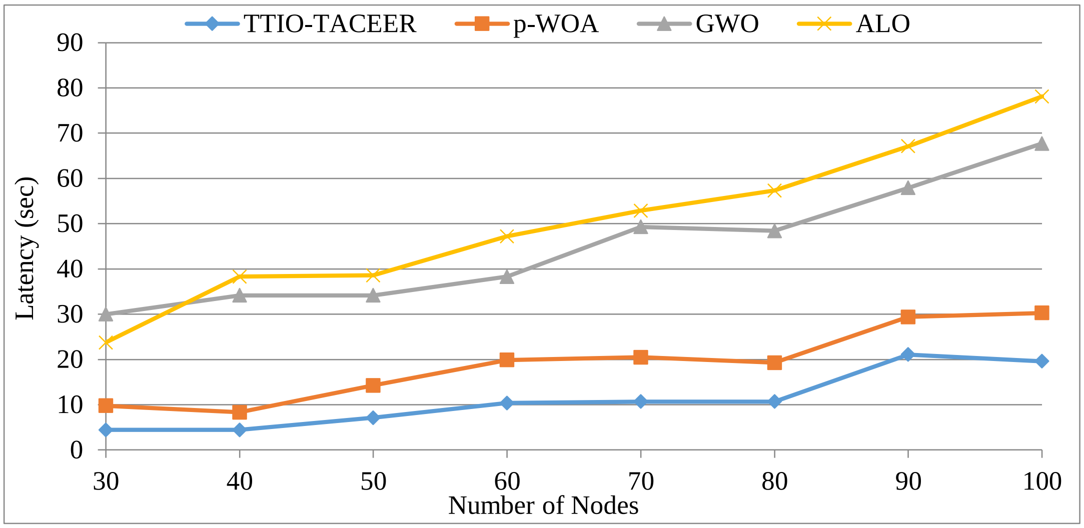

Fig. 6 LAT outcome of the TTIO-TACEER approach under various nodes

In Table 5 and Figure 7, the performances of the TTIO-TACEER methodology are associated in terms of average throughput (ATHR). The values of the table revealed that the ALO and GWO techniques have resulted in poor performance with diminished ATHR values. Also, the p-WOA approach has accomplished discreetly closer ATHR values. However, the TTIO-TACEER model highlights its supremacy with maximum ATHR of 2.373MBPS, 4.748MBPS, 6.623MBPS, 6.779MBPS, 5.623MBPS, 6.779MBPS, 7.966MBPS, and 7.685MBPS below nodes 30-100, respectively.

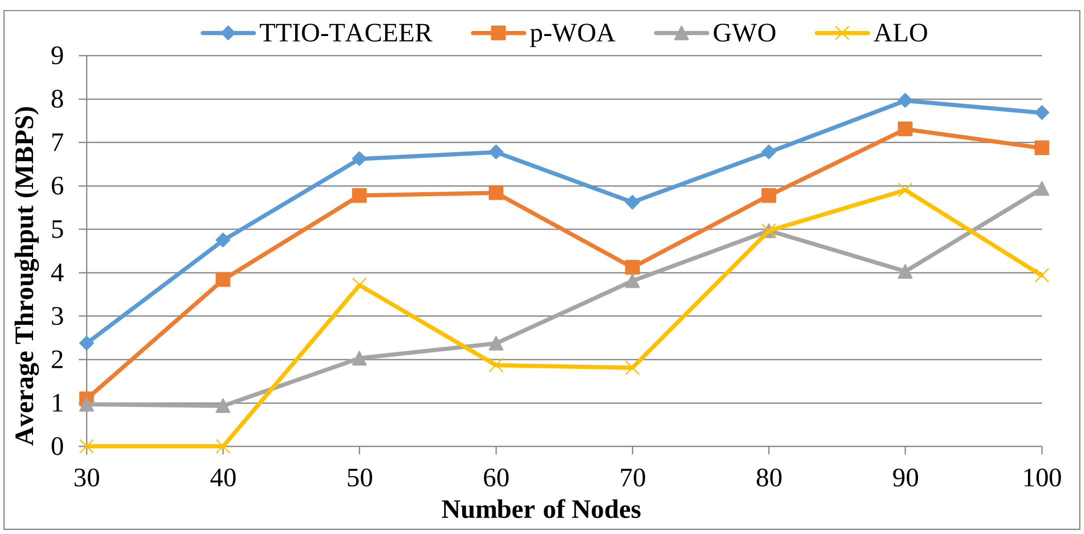

Fig. 7 ATHR outcome of the TTIO-TACEER approach under various nodes

Table 5. ATHR outcome of the TTIO-TACEER approach with existing models under various nodes

ATHR (MBPS)				
Number of Nodes	**TTIO-TACEER**	**p-WOA**	**GWO**	**ALO**
30	2.373	1.092	0.968	0.001
40	4.748	3.842	0.936	0.002
50	6.623	5.779	2.030	3.717
60	6.779	5.842	2.373	1.874
70	5.623	4.123	3.811	1.811
80	6.779	5.779	4.967	4.967
90	7.966	7.310	4.029	5.904
100	7.685	6.873	5.935	3.936

Table 6 and Figure 8 suggest the Load Balancing Factor (LBF) performances of the TTIO-TACEER technique with existing methodologies. The performances concluded that the TTIO-TACEER method recognizes better performance with decreased LBF values. Using 100 TR, the TTIO-TACEER method gained a diminished LBF of 0.0017, but the GWO, ALO, and p-GWO methodologies reached superior LBF of 0.0053, 0.0053, and 0.0087. Likewise, using 600 nodes, the TTIO-TACEER method gained decreased LBF of 0.1084, but the GWO, ALO, and p-GWO methodologies attained increased LBF of 0.2870, 0.1466, and 0.1220.

Table 6. LBF outcome of the TTIO-TACEER approach with existing models under various TR

LBF				
Transmission Range	**GWO**	**ALO**	**p-WOA**	**TTIO-TACEER**
100	0.0053	0.0053	0.0087	0.0017
150	0.0061	0.0053	0.0053	0.0001
200	0.0061	0.0053	0.0087	0.0035
250	0.0096	0.0070	0.0269	0.0009
300	0.0200	0.0200	0.0365	0.0070
350	0.0365	0.0287	0.0373	0.0174
400	0.0694	0.0512	0.0963	0.0261
450	0.1067	0.0616	0.1379	0.0460
500	0.1561	0.1041	0.1180	0.0807
550	0.1370	0.2566	0.1197	0.1076
600	0.2870	0.1466	0.1220	0.1084

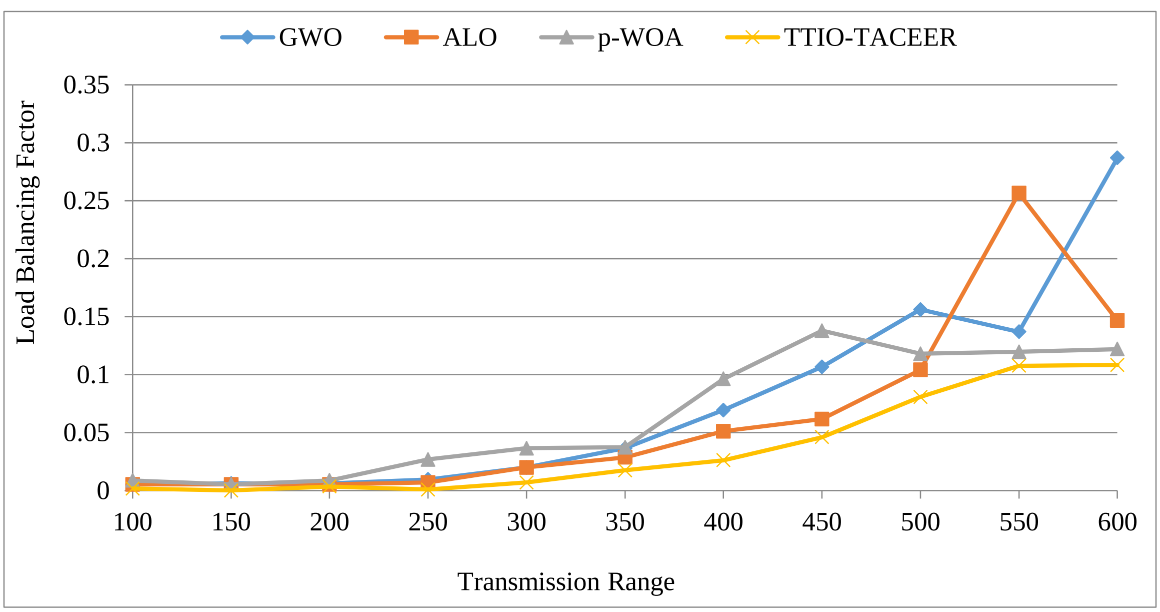

Fig. 8 LBF outcome of the TTIO-TACEER approach under various TR

5. Conclusion

In this study, the TTIO-TACEER model in VANET is proposed. The main purpose of the TTIO-TACEER model is to integrate an optimized clustering mechanism with an efficient routing strategy to enhance network performance and reliability. In the clustering phase, the TTIO-TACEER technique is applied using the GO to select optimal CHs. Next, the multi-criteria FF considers RE, TL, DD, TEC, and mobility for cluster formation. In the routing phase, the TTIO-TACEER technique is implemented using the concept of the NiOA, which is employed to optimize routing paths between CHs and the BS.

Moreover, the routing FF considers the distance to the BS to improve data transmission reliability while reducing LAT. An extensive simulation validation is executed to highlight the significance of the TTIO-TACEER technique. A brief comparative study described the superior results of the TTIO-TACEER technique when compared to other existing models. The TTIO-TACEER technique exhibits limitations in its dependency on idealized network conditions, which may not fully capture real-world environmental factors such as interference and hardware failures.

Furthermore, heterogeneous node capabilities and the scalability of massive networks are not sufficiently examined. Future studies may explore integration with ML models for adaptive parameter tuning and integrate security mechanisms to counteract advanced attacks. Practical applications comprise environmental monitoring, smart agriculture, and industrial automation, where efficient and reliable WSNs are critical for real-time data collection and decision-making.

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