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Hybridization of Brownboost and Random Forest Tree with Gradient Free Optimization for Route Selection

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ABSTRACT MANETs are self-organizing network architectures of mobile nodes. Due to node mobility, wireless network topologies dynamically various over time. A novel link stability estimation technique called Hybridization of Brownboost Cluster and Random Forest Decision Tree with Optimized Route Selection (HBCRFDT-GORS) technique is introduced for increasing the reliable data delivery by eliminating the stale routes in MANET. Brown Boost technique is applied to find the route paths having the smaller number of hop counts to perform the data transmission. After that, the status of the mobile nodes in the selected route paths is determined based on the residual energy and signal strength. Then, a random forest decision tree is applied to correctly identify the stale routes by finding the link failure due to the selfish node and the corruptive node along the route path. Then the broken link is removed from the route path. After eliminating the stale route from the path, the HBCRFDT-GORS technique finds the alternative optimal route through the gradient free optimization. The proposed HBCRFDT-GORS technique performs stale route elimination and improves reliable data delivery from source to destination. Simulation is conducted on different performance metrics such as routing overhead, packet delivery ratio, packet drop rate, and delay with respect to the number of data packets. The Network simulation results indicate that the HBCRFDT-GORS technique is improving the data delivery and and minimizing the delay as well as reducing the packet losses when compared to the baseline approaches.

KEYWORDS MANET; Stale route elimination; Hybridization of Brownboost Cluster; Random Forest Decision Tree; Gradient Free optimization.

I. INTRODUCTION

MANET is a wireless communication network in which the nodes connect to any device at any specified time. The mobile nodes are closest to the transmission range directly communicates with the data through the intermediate nodes. The data communication between the nodes requires the shortest path and it consumes minimum energy. A routing path is built, with the source node transmitting information through a less intermediate node to reach the destination node for successful communication with lesser delay. In MANETs, the node connection breaks are recurrent because of the entire nodes are in movement. The following section presents many routing algorithm and its fewer limitations.

The volunteer Nodes of Ant Colony Optimization Routing (VNACO) technique was introduced in [1] with the aim of minimizing both the delay and routing overhead while distributing the data from source to destination. The designed VNACO technique increases the throughput and reduces the routing overhead but the higher delivery ratio was not achieved. In [2], a K-means cluster formation firefly cluster head selection based MAC routing protocol (KF-MAC) was introduced to attain the efficient data packet transmission with lesser energy utilization. However, the deigned KF-MAC routing protocol failed to achieve the higher data packet forwarding with lesser delay.

The energy-aware on-demand routing protocol (EA-DRP) was deveoped in [3] to ensure the data transmission with minimum packet loss. However, the designed protocol failed to apply the optimization technique for achieving higher data delivery. An efficient power-aware routing (EPAR) technique was developed in [4] for increasing the reliability of data packets forwarding on a particular link. But, the performance of throughput was not estimated. Opposition genetic-based fish swarm optimization (OGFSW) technique was introduced in [5] for increasing the data transmission with lesser energy consumption. But the technique failed to minimize the performance of packet loss since it failed to find the link stability.

The Optimized energy-efficient route assigning (OEERA) technique was designed in [6] to offer a better and energy-efficient routing path selection. However, the designed method failed to implement a better optimization scheme for finding an optimal path. A Hybrid model based multipath routing (HM-MPR) method was introduced in [7] to increase the effectiveness and reliability of routing with lesser overhead. However, the method failed to perform the delay tolerance in MANET.

An integration of the Ad-hoc On-Demand Distance Vector (AODV) protocol with Ant Colony Optimization (ACO) was developed in [8] to select the optimal route for transmission of the data packets. But the received signal strength of the node was not considered to reduce the routing overhead. Reliable Path Selection approach was designed in [9] for the data packet communication with less amount of energy and time consumption. But the instable link and mobility character of the nodes causes the link failure. An evolutionary self-cooperative trust (ESCT) method was developed in [10] to enhance the network scalability and ensures reliable routing with higher packet delivery. The designed method failed to reduce packet loss. A Constructive-Relay-based CooPerative Routing (CRCPR) protocol was introduced in [11] to accomplish the better data transmission. However, the optimal route selection was not performed. A Reliable opportunistic routing technique was developed in [12] to enhance the data transmission. However, it was complex to achieve a reliable packet delivery in MANETs.

A new bio-inspired hybrid trusted routing protocol was developed in [13] for effectively finds the routes to distribute the packets to the destination. However, the designed protocol failed to consider extending link status metrics. A Graph Kernel-based Clustering Algorithm was designed in [14] for efficient data packet transmission. The designed clustering algorithm failed to develop the algorithm comprises the support of nodes with limited mobility. An On-demand multipath routing protocol was designed in [15] to enhance the data transfer on a stable path. However, it failed to develop a heuristic routing algorithm that allows the nodes to infer topology changes based on parameter changes.

A distributed dynamic routing algorithm was designed in [16] to create an efficient routing mechanism based on mobility of nodes. However, the designed routing algorithm has some defects in terms of delay and packet loss rate. A stable and energy-efficient routing algorithm was introduced in [17] for MANET. The designed routing algorithm failed to implement the optimization technique for enhancing the packet delivery ratio. A stable connected dominating set (CDS) construction algorithm was designed in [18] to improve the data transmission through the neighborhood. The energy-optimized data transmission remained unaddressed. A Multi-constraints Link Stable Multicast Routing protocol was developed in [19] to improve the data delivery and minimize the delay. But it failed to enable well link connectivity between the nodes. A cross-layer Multicast Routing (CLMR) was designed in [20] to enhance the QoS aware routing but it has higher overhead. The above-said issues are addressed by introducing a novel HBCRFDT-GORS technique.

II. HYBRIDIZATION OF ROWNBOOST CLUSTER AND RANDOM FOREST DECISION TREE

A MANET permits the mobile nodes to construct a wireless network without any fixed infrastructure. In MANETs, whenever the neighbor nodes travel out of other node communication range, the connection between the mobile nodes is broken. Thus it creates a delay and packet loss in the network. An HBCRFDT-GORS technique is introduced in this section where three processes are carried out. Figure 1 illustrates the block diagram of the HBCRFDT-GORS technique to perform data transmission with lesser delay. Three processes are included in the HBCRFDT-GORS technique such as Route path discovery, stale route elimination, and optimal route selection. The Brown boost clustering technique is applied for Route path discovery. Secondly, stale route elimination is carried out by applying a random forest decision tree classifier. Finally, gradient free optimization is applied to find the optimal route path. Three processes of the HBCRFDT-GORS technique is described in the following sections.

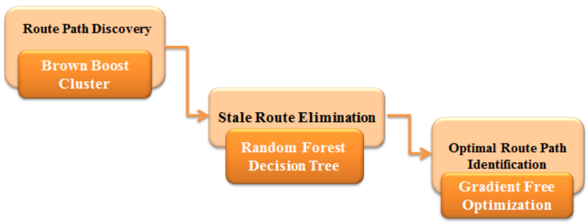

Figure 1. Block Diagram of HBCRFDT-GORS Technique

A. BROWNBOOST TECHNIQUE BASED ROUTE PATH DISCOVERY

The proposed HBCRFDT-GORS technique starts to perform the route discovery by establishing the multiple route paths between the source and destination Then the Brown Boost technique is applied to find the best route paths having the smaller number of hop counts to perform the data transmission with minimum delay. The Brown Boost is a machine learning ensemble algorithm that provides strong results by combing the weak learners.

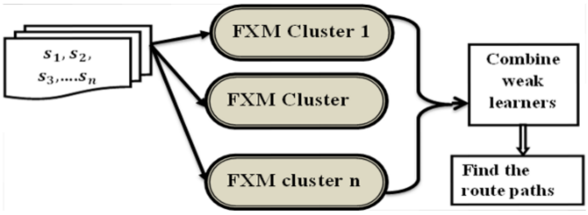

Figure 2. Brown Boost Ensemble Technique

Figure 2 given above illustrates the Brown Boost ensemble clustering technique to efficiently identify the route paths. Let us consider the multiple route paths r_1, r_2, r_3... r_n. The Brown Boost ensemble clustering technique comprises a set of weak clusters $Q_1, Q_2, Q_3 \ldots Q_n$. A fuzzy x-means (FXM) clustering technique is used as a weak learner for grouping the route paths based on the number of hop counts. Initially, x number of clusters $C_1, C_2, C_3 \ldots C_x$ and centroid $f_1, f_2, f_3 \ldots f_x$ are initialized in a random manner. Then the FXM algorithm satisfies the below objective function,

$$\mathrm{Q} = arg\ min \sum_{i=1}^{n} \sum_{j=1}^{x} \mu_{ij} \left| r_i - f_j \right|^2, \tag{3}$$

where Q denotes an output of weak learner, $arg\ min$ denotes an argument of a minimum function, μ_{ij} denotes a fuzzy membership function $\mu_{ij} \in [0,1]$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{m} \left(\frac{\|r_i - f_j\|}{\|r_i - f_k\|} \right)^{\frac{2}{\alpha - 1}}}, \tag{4}$$

where, μ_{ij} designates a membership function, Here, $\|r_i - f_j\|$ denotes a distance between 'i^{th}' data and'j^{th}' cluster centroid, $\|r_i - f_k\|$ indicates a distance between 'i^{th}' data and 'k^{th}' cluster centroid and 'α' denotes a fuzzifier that is represented as '$a > 1$. The path which is closer to the centroid is grouped into the cluster. Similarly, all the route paths are grouped based on the hop counts. In order to improve the clustering accuracy, the weak clusters are grouped into a strong one. The output of each weak clusters are summed and it is expressed as follows,

$$Z = \sum_{i=1}^{n} Q_i \ , \tag{5}$$

where, Z indicates an ensemble clustering results, Q_i denotes an output of the weak cluster. After that, the weight is set to the weak clusters.

$$\delta = \exp\left(-\frac{(r_i\,(s_i) + w)^2}{b} \right). \tag{6}$$

From (6), δ represents the weight of the ensemble classifier, $r_i\ (s_i)$ denotes the margin of the path between the clusters, 'w' denotes an amount of remaining time of the base cluster $(w = b)$.

After assigning the weight, the Mean Squared Error Loss is measured for each weak learner to obtain the final strong classification results. The Mean Squared Error Loss is calculated as the average of the squared differences between the predicted and actual results given below,

$$L_{MSE} = [A_t - P_r]^2, \tag{7}$$

where, L_{MSE} denotes a Mean Squared Error Loss, A_t indicates actual results, P_r indicates predicted results. Based on the error value, the weights get updated based on the Mean Squared Error Loss. If the base cluster incorrectly groups the route paths, then the weight gets increased. Otherwise, the weight is reduced. As a result, the brown boost ensemble technique correctly clusters the route paths and identifies the route paths which have the less number of hops.

B. RANDOM FOREST DECISION TREE ENSEMBLE TECHNIQUE BASED STALE ROUTE ELIMINATION

Once the route paths are identified with less number of hop counts, a random forest decision tree is applied to identify the stale routes by finding the link failure due to the selfish node and the corruptive node along the route path. The HBCRFDT-GORS technique uses the Random forest decision tree ensemble technique to perform stale route elimination. A random forest decision tree is a bootstrap aggregating technique to improve the accuracy of classification.

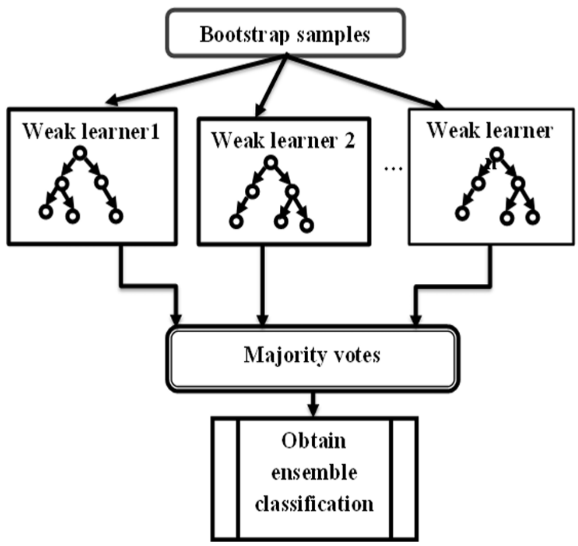

Figure 3. Random forest decision tree ensemble techniques

Figure 3 portrays the Random forest decision to find the stale route due to the selfish nodes and other nodes. The random forest decision tree uses the bootstrap sample as the training set (i.e. the number of mobile nodes in the path) and constructs the weak learners as a decision tree to analyze the node behaviors such as cooperative communication, trust level. A decision tree is a decision support tool which comprises the root node, internal node, and leaf node. The root node is the uppermost node in the tree and it has no parent. The root node "test" on an attribute (e.g. whether a node has better cooperativeness and trust level), each branch indicates a result of the test, and finally, the leaf node provides a class label (decision after verifying cooperativeness and trust level).

Initially, the cooperativeness of the mobile node is determined through the actions performed by the node while communicating with other mobile nodes along the route path. The misbehavior nodes did not cooperate for efficient data transmission. Before the data transmission, the cooperativeness is determined. For each node transmits the beacon message to other nodes over the time instant,

$$mn_i \overset{\mathrm{B_t}}{\Rightarrow} mn_j, \quad (11)$$

where, B_t symbolizes the beacon message sent from the mobile node mn_i to another mobile node mn_j. Upon successful reception of beacon message, the mobile node mn_jsends the reply.

$$mn_i \overset{\mathrm{B_r}}{\Leftarrow} mn_j \ , \quad (12)$$

where, B_r denotes a reply beacon message. If the mobile node mn_jdid not send any reply at particular time instances, then the node mn_j does not cooperate with the node mn_i at a time 't' and it stops the data forwarding to other nodes. Similarly, the trust level of the node is estimated as given below,

$$T_n = \left(\frac{P_{forward} - P_{Drop}}{P_{received}}\right), \quad (13)$$

where, T_n indicates a trust level, $P_{forward}$ indicates a data packet forwarded, P_{Drop} represents a data packet dropped, $P_{received}$ symbolizes a data packet received by the node. The root node test whether a mobile node has better cooperativeness and higher than the trust level is classified as a normal node. Otherwise, the node is said to be a suspicious node or corruptive node.

$$D = \begin{cases} better\ CO \text{ and } (T_n > th),\ NN \\ \quad Otherwise \quad ,SN\ or\ CN \end{cases}, \quad (14)$$

where D indicates the classification results of the decision tree, the node having better cooperative communication (CO) and a higher trust T_n than the threshold *(th)* is classified as a normal node(*NN*) Otherwise, the nodes are classified as suspicious nodes (*SN*) and corruptive nodes (*CN*). In order to improve the accurate classification, weak learner results are combined into strong.

$$R = \sum_{i=1}^{g} D_i \ . \quad (15)$$

From (15), R indicates ensemble classification results, and D_i signifies the output of all the decision tree classifiers. Then the voting method is applied to find the accurate classification results. The majority votes of the samples are formulated as below,

$$G = \underset{g}{arg\ max}\ v\ (n_i). \quad (16)$$

From (16), G indicates ensemble classification results, *arg max* indicates an argument of the maximum function to find the majority votes (v)f the nodes whose decision known to the last g^{th} weak learner. As a result, the nodes have the majority votes results are taken as final classification results. Finally, the Random forest decision technique provides the majority results as final results. Therefore, the selfish node or corruptive node in the route path causes the link failure and it only aware of the agent node. If any link failure, the mobile agents' node distributes an error message (r_{err}) regarding the broken link to all the other mobile nodes within the covered region. This broken-link is removed from the route path for better data delivery.

Algorithm 1 explains the process of the Random forest decision tree ensemble classification to remove the stale route from the cache. Initially, the decision trees are constructed by analyzing the behavior of the mobile node in the selected route paths. The node having the better cooperativeness and trust value is classified as a normal' and the link between the nodes is stable. Otherwise, the nodes are classified as a suspicious node 'or 'corruptive node' and the links are not stable. If any route failure, the mobile agent (*MA*) distributes the error $\boldsymbol{r_{err}}$ message and remove the unstable route from the cache. As a result, the stable route is selected and removes the other routes in MANET.

Algorithm 1: Random forest decision tree ensemble techniques
Input: Number of routes paths in caches $\mathrm{r_1, r_2, r_3, \dots r_n}$ **Output:** Eliminate the stale routes
Begin 1. **For each** route $\mathrm{r_i}$ in cache 2. Construct decision trees 3. **for** node mn_i and node mn_j 4. Measure node cooperativeness 5. Measure trust level T_n 6. **If** ($better\ CO$ && ($T_n > th$))**then** 7. Node is classified as 'normal' 8. **Else** 9. Node is classified as 'suspicious node ' or 'corruptive node' 10. **End if** 11. **End for** 12. **End for** 13. *MA* distributes r_{err} message to all the nodes 14. Eliminate stale route from route-cache **End**

C. GRADIENT FREE OPTIMIZATION BASED OPTIMAL ROUTE PATH SELECTION

After eliminating the stale route from the path, the HBCRFDT-GORS technique finds the alternative optimal route through the gradient Free optimization to solve both constrained and unconstrained problems. While considering the large population, the algorithm runs in a constrained mode i.e. iteration count is preset. When the population count is small, the algorithm runs in an unconstrained mode i.e. no iteration count is preset. Gradient Free optimization algorithm is a metaheuristic technique and population-based method which frequently changes a population of individual solutions. On the contrary to the conventional optimization algorithm, gradient free optimization does not utilize any hyperparameters. The hyperparameter is a parameter and the value is preset before starting the learning process.

The algorithm initializes the population of the nodes with multiple links $L_1, L_2, L_3 \ldots L_n$ is defined in the search space. After the initialization, the best and worst solution is identified based on the objective function. Here the objective function is measured based on the link connectivity between the nodes,

$$L(t) = \left[\frac{t_r}{D_{mn}}\right], \tag{17}$$

where, $L(t)$ indicates link connectivity between the node at a time t. t_r denotes a transmission range of the node, Dmn indicates a distance between the two-node i and node j. The transmission range is greater than the distance (i.e. $t_r > D_{mn}$). If the link $L_i(t)$ is connected at time 't' is greater than the link of $L_j(t)$ i.e. $L_i(t) > L_j(t)$, then replace the worst solution and accepts the best solution as follows,

$$L_i(t)' = L_i(t) + k_1(|L_{best} - L_i(t)|) - k_2(|L_{worst} - L_i(t)|), \tag{18}$$

where, $L_i(t)'$ indicates an updated solution, $L_i(t)$ is the current solution, k_1, k_2 are the two random numbers in the ranges from [0,1], $\left(\left|L_{,best} - L_{ij}(t)\right|\right)$ the term indicates a tendency of the current solution $L_{ij}(t)$ move closer to the best solution L_{best}, $\left|L_{worst} - L_{ij}(t)\right|$ the terms indicate a tendency of the current solution $L_i(t)$ move closer to the worst solution. Based on the best conditions, the current solution is replaced by the previous solution. In other words, the link with better connectivity is selected and it is said to a stable for data transmission. This process gets repeated until it reaches the maximum iteration. Based on this analysis, the proposed HBCRFDT-GORS technique performs stale route elimination and improves reliable data delivery from source to destination. The flow chart for gradient Free optimization based optimal route path selection is illustrated in figure 5. Figure 4 demonstrates the flow chart of the Gradient Free optimization-based alternate route path selection for improving the data delivery and minimizes the packet loss. The algorithmic process of the gradient Free optimization based optimal route path selection. The algorithm 2 clearly describes the step by step process of the Gradient Free optimization based optimal alternate route path selection. The link connectivity between the nodes is measured and finds the best link and removes the the worst link. The best links between the nodes are chosen as optimal to perform the data transmission resulting in it reduces the end-to-end delay.

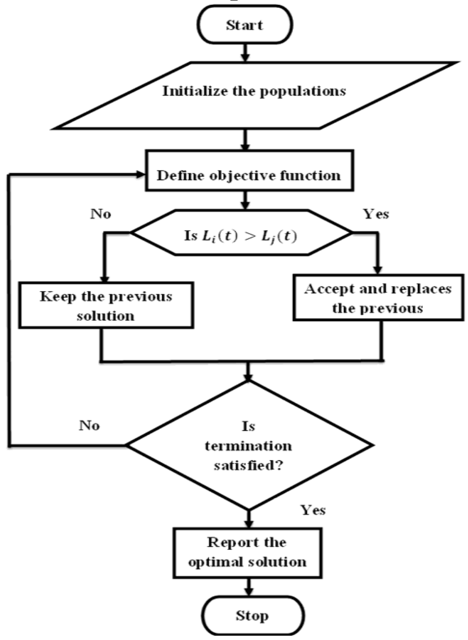

Figure 4. Flow chart of Gradient Free optimization based optimal route path selection

Algorithm 2: Gradient Free optimization based optimal route path selection

Input: Nodes with multiple links $L_1, L_2, L_3, \ldots . L_n$
Output: select optimal alternate link

Begin

1. **Initialize the population of the** $L_1, L_2, L_3, \ldots . L_n$
2. **For each** link between the node
3. Define objective function '$L(t)$'
4. **If** ($L_i(t) > L_j(t)$) **then**
5. Update the solution $L_i(t)'$
6. Accept the current best and replaces the worst solution
7. **else**
8. Keep the previous solution
9. **End if**
10. **If** (Is termination satisfied) **then**
11. Return optimal link between the nodes
12. **Else**
13. Go to step 3
14. **End if**
15. **End for**

End

III. SIMULATION SETTING

In this section, the simulation of the proposed HBCRFDT-GORS technique and existing VNACO [1], KF-MAC [2] are implemented using the NS2.34 network simulator. In order to conduct the simulation, mobile nodes are deployed in the square area $(1100\,m * 1100\,m)$. The simulation set up is illustrated in Table1.

Table 1. Simulation Setting

Simulation parameters	Values
Network Simulator	NS2.34
Simulation area	1100 m * 1100 m
Number of mobile nodes	50,100,150,200,250,300, 350,400,450,500
Number of data packets	25,50,75,100,125,150,175,200,225, 250
Mobility model	Random Waypoint model
Nodes speed	0 – 20 m/s
Simulation time	300sec
Routing Protocol	DSR
Number of runs	10

IV. PERFORMANCE EVALUATION

Routing overhead

It is measured as an amount of time taken by the algorithm to broadcasts the data packets from the source to the destination. Figure 5 illustrates the performance of routing overhead versus the number of data packets being transmitted from source to destination.The overall performance results indicate that the routing overhead of the HBCRFDT-GORS technique is comparatively lesser than the other techniques.

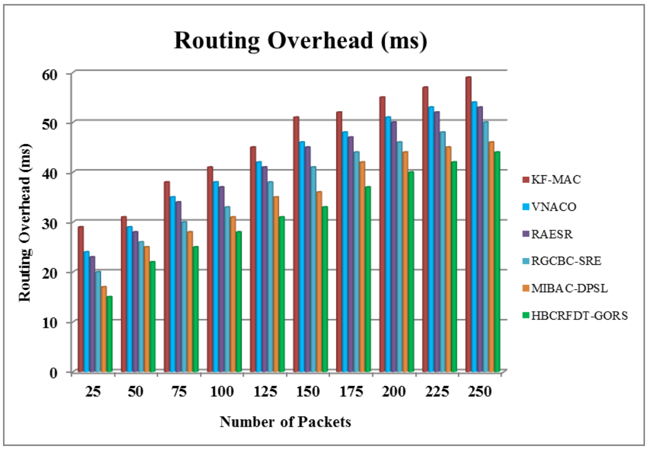

Figure 5. Comparison of routing overhead

The significant reason is that the HBCRFDT-GORS technique uses the brownboost ensemble clustering technique to find the optimal route paths with the least count of the hop counts between the source and destination. The path which has lesser hop counts minimizes routing overhead taken for the data transmission from source to destination.

Packet Delivery Ratio

It is estimated as a ratio of the number of packets effectively received to the total number of data packets sent. Figure 6 exhibits the performance analysis of the packet delivery ratio of the HBCRFDT-GORS technique. The overall assessment results indicate that the HBCRFDT-GORS technique outperforms well in terms of achieving a higher delivery ratio. This improvement is achieved by selecting the route path with lesser hop counts. Then the energy-efficient and better signal strength of the node is identified for continuous data delivery. Besides, the suspicious or corruptive nodes are identified by applying the random forest ensemble classifier based on trust and cooperative communication.

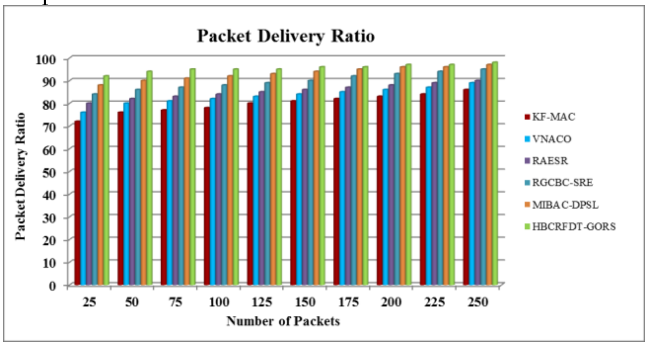

Figure 6. Packet Delivery Ratio

The stale route is determined and it removed from the cache. Alternative routes are chosen using Gradient Free optimization technique. is applied to find alternative routes with better link connectivity is chosen for efficient transmission. As a result, the successful delivery rate is achieved.

Packet Drop Rate

It referred to as the ratio of data packets dropped from the total number of packets sent from the source node.

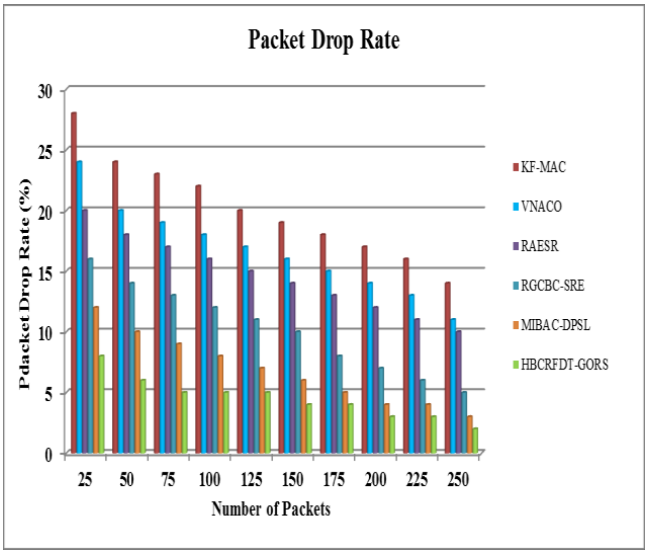

Figure 7. Packet drop rate

Figure 7 demonstrate that the simulation analysis of the packet drop rate versus the number of data packets. The simulation results prove that the packet drop rate is considerably minimized than the other methods. HBCRFDT-GORS technique achieves a lesser drop rate due to the elimination of the stale routes from the route cache.

Delay

It is defined as the difference between the arrival time of the destination and the transmitting time of the packet. Figure 8 depicts the convergence chart of delay.The HBCRFDT-GORS technique reduces the delay than the other methods due to the application of agent-based optimal stale route elimination and optimum route path discovery. Stale route paths are removed alternate route path is selected between the nodes which result it in increases the data delivery and it also reduces the delay.

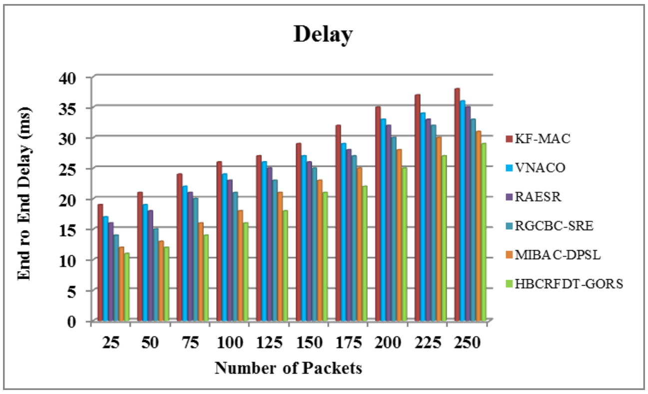

Figure 8. Delay

V. CONCLUSION

The proposed HBCRFDT-GORS technique to eliminate the stale routes through hybridization of brownboost cluster and random forest decision tree classifier. Stale route elimination is essential for increasing data transmission in MANET. To overcome the challenges of Stale routes, a brownboost cluster to analyze the route paths based on the hop counts. Random forest decision tree analyse the stale routes, based on the identification stale routes are eliminated and alternative paths are chosen using Gradient Free optimization to improve the data delivery and minimizes the delay. Simulation result shows that the proposed HBCRFDT-GORS technique is more efficient than the other baseline algorithms.

REFERENCES

[1] N. Noor Alleema & D. Siva Kumar, "Volunteer nodes of ant colony optimization routing for minimizing delay in peer to peer MANETs," *Peer-to-Peer Networking and Applications*, Springer, vol. 13, pp. 590– 600, 2020. https://doi.org/10.1007/s12083-019-00772-w.

[2] M. Rao and N. Singh, "Energy efficient QoS aware hierarchical KF-MAC routing protocol in MANET," *Wireless Personal Communications*, Springer, vol. 101, issue 2, pp. 635–648, 2018. https://doi.org/10.1007/s11277-018-5708-3.

[3] Rajendra Prasad P. and S. Shankar, "Efficient performance analysis of energy aware on demand routing protocol in mobile ad-hoc network," *Engineering Reports*, Wiley, vol. 2, issue 3, pp. 1-14, 2020. https://doi.org/10.1002/eng2.12116.

[4] L. Femila and M. Marsaline Beno, "Optimizing transmission power and energy efficient routing protocol in MANETs," *Wireless Personal Communications*, Springer, vol. 106, pp. 1041–1056, 2019. https://doi.org/10.1007/s11277-019-06202-7.

[5] M. Rajashanthi and K. Valarmathi, "Energy-efficient multipath routing in networking aid of clustering with OGFSO algorithm," *Soft Computing*, vol. 24, pp. 12845–12854, 2020. https://doi.org/10.1007/s00500-020-04710-4.

[6] R. Aruna, R. Subramanian, P. Sengottuvelan, J. Shanthini, "Optimized energy efficient route assigning method using related node discovery algorithm in MANET," *Cluster Computing*, Springer, vol. 22, pp. 469-479, 2019. ttps://doi.org/10.1007/s10586-018-2520-5.

[7] N.S. Saba Farheen, A. Jain, "Improved routing in MANET with optimized multi path routing fine tuned with hybrid modeling," *Journal of King Saud University – Computer and Information Sciences*, Elsevier, pp. 1-8, 2020. https://doi.org/10.1016/j.jksuci.2020.01.001.

[8] D. Sarkar, S. Choudhury, A. Majumder, "Enhanced-Ant-AODV for optimal route selection in mobile ad-hoc network," *Journal of King Saud University – Computer and Information Sciences*, Elsevier, pp. 1-16, 2018. https://doi.org/10.1016/j.jksuci.2018.08.013.

[9] M. Anbarasan, S. Prakash, M. Anand, A. Antonidoss, "Improving performance inmobile ad hoc networks by reliable path selection routing using RPS-LEACH," *Concurrency and Computation: Practice and Experience*, Wiley, vol. 31, issue 7, pp. 1-11, 2019. https://doi.org/10.1002/cpe.4984.

[10] R. J. Cai, X. J. Li, P. H. J. Chong, "An evolutionary self-cooperative trust scheme against routing disruptions in MANETs," *IEEE Transactions on Mobile Computing*, vol. 18, issue 1, pp. 42–55, 2019. https://doi.org/10.1109/TMC.2018.2828814.

[11] J. Bai, Y. Sun, C. Phillips, and Y. Cao, "Toward constructive relay-based cooperative routing in MANETs," *IEEE Systems Journal*, vol. 12, issue 2, pp. 1743–1754, 2018. https://doi.org/10.1109/JSYST.2017.2721543.

[12] D. Kang, H.-S. Kim, C. Joo, S. Bahk, "ORGMA: Reliable opportunistic routing with gradient forwarding for MANETs," *Computer Networks*, Elsevier, vol. 131, pp. 52-64, 2018. https://doi.org/10.1016/j.comnet.2017.12.001.

[13] M. Zhang, M. Yang, Q. Wu, R. Zheng, J. Zhu, "Smart perception and autonomic optimization: A novel bio-inspired hybrid routing protocol for MANETs," *Future Generation Computer Systems*, Elsevier, vol. 81, pp. 505-513, 2018. https://doi.org/10.1016/j.future.2017.07.030.

[14] Y. Song, H. Luo, S. Pi, C. Gui, B. Sun, "Graph kernel based clustering algorithm in MANETs," *IEEE Access*, vol. 8, pp. 107650–107660, 2020. https://doi.org/10.1109/ACCESS.2020.3001137.

[15] Z. Chen, Wenli Zhou, S. Wu, L. Cheng, "An adaptive on-demand multipath routing protocol with QoS support for high-speed MANET," *IEEE Access*, vol. 8, pp. 44760–44773, 2020. https://doi.org/10.1109/ACCESS.2020.2978582.

[16] N. Wang, H. Zhao, L. Hai, "Distributed routing algorithm with dynamic connection partition for mobile ad hoc networks," *IET Networks*, vol. 8, issue 4, pp. 239–245, 2019. https://doi.org/10.1049/iet-net.2018.5150.

[17] S. Hao, H. Zhang, M. Song, "A stable and energy-efficient routing algorithm based on learning automata theory for MANET," *Journal of Communications and Information Networks*, Springer, vol. 3, pp. 52-66, 2018. https://doi.org/10.1007/s41650-018-0012-7.

[18] H. Zheng, C. Gao, Y. Yan, B. Chai, "An algorithm to construct minimum velocity based stable connected dominating sets for MANETs using strong neighborhoods," *Procedia Computer*, Elsevier, vol. 174, pp. 591-596, 2020. https://doi.org/10.1016/j.procs.2020.06.129.

[19] G. Singal, V. Laxmi, M.S. Gaur, S. Todi, V. Rao, M. Tripathi, R. Kushwaha, "Multi-constraints link stable multicast routing protocol in MANETs," *Ad Hoc Networks*, Elsevier, vol. 63, pp. 115-128, 2017. https://doi.org/10.1016/j.adhoc.2017.05.007.

[20] D. Chander, R. Kumar, "QoS enabled cross-layer multicast routing over mobile ad hoc networks," *Procedia Computer Science*, Elsevier, vol. 125, pp. 215-227, 2018. https://doi.org/10.1016/j.procs.2017.12.030.

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