Probit Based Grey Wolf Optimal Route Path Discovery In Internet Of Vehicles

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Abstract: Internet of Things (IoT) is a communication technology that enables the devices as vehicles being connected called as Internet of Vehicles (IoV) for allowing the data communication in the intelligent transportation system. IoV communicates with each other to identify the current status of the road and vehicle for real-time traffic comfort and safety. Due to the increasing number of vehicles in city road networks, efficient neighbor identification and finding of the best available path in the highly unstable vehicular environment are the major problems. An efficient technique called Probit Regressive Chaotic Bio-inspired Grey Wolf Optimization (PRCBGWO) technique is introduced to improve the reliable data transmission and minimize the end to end delay in IoV. The PRCBGWO technique performs neighboring location identification and optimal route path discovery. At first, vehicle nodes characteristics such as distance, signal strength and angle of direction are calculated. Then the Probit Regression is applied by analyzing the node characteristics and identifies the neighboring nodes from source to destination. Next the multiple route paths are constructed through the route request and reply message distribution between source and destination. Finally, Multi-Objective Chaotic Grey Wolf Optimization technique is applied to discover the optimal route path among the available paths with multiple objective functions such as path length and bandwidth availability. A reliable route path from source to destination is identified through the neighboring vehicles. After that, the data packets are transmitted along the selected route path to the destination node. This helps to improve packet delivery and minimize loss and end to end delay. The simulation is carried out with different metrics such as packet delivery ratio, packet loss rate, average end to end delay and throughput based on a number of data packets. The observed results confirm that the PRCBGWO technique increases the packet delivery ratio, throughput and minimizes the end to end delay, as well as packet loss than the state-of-the-art methods.

Index Terms: Internet of Vehicles (IoV), VANET, neighboring location detection, Probit Regression,

1. INTRODUCTION

Internet of Vehicles (IoV) model is a subset of Internet of Things (IoT) technology. IoV is broadly used in several applications such as communications, transportation, automotive technology and so on. In VANET, IoV is a promising technology that provides the solutions for traffic control systems to monitor road conditions and travel journey. The architecture of the IoV is shown in figure 1.

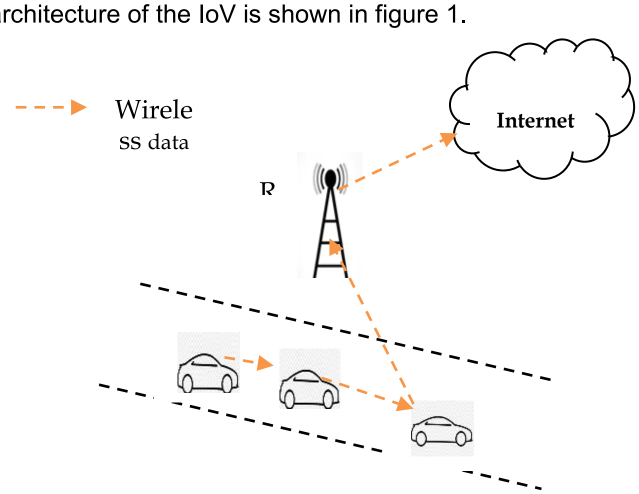

Figure 1 *Architecture of IoV*

Figure 1 shows the typical network structure of IoV, including three types of communication such as Vehicle-to-vehicle , Vehicle-to-Road Side Unit (RSU) and Road Side Unit to the internet. The vehicles are positioned for directly sharing the data via wireless communications. In order to connect the vehicles on roads, RSUs are established in urban roads where it is operating as routers and it is stationary after a deployment that helps to upload the data generated by vehicles. Then the information is sent to the remote data center through the internet for further processing. In order to perform the data transformation from source to destination, the neighboring location and the optimal route path identification plays a challenging issue in VANET. The Identical Destination Based Community in the Internet of Vehicles (IDCIoV) was developed for identifying the optimal path. The performance of throughput was not maximized since the designed method failed to effectively select the optimal path. The remainder of the paper is structured into five different sections. Section 2 presents related works. Section 3 describes the proposed PRCBGWO technique to overcome the existing routing problem. Section 4 gives the simulation results and discussions of the various parameters are presented in section 5. Section 6 concluding remarks of the paper.

PROPOSED WORK

The issues from the existing literature are solved by designing a proposal called PRCBGWO technique. The most important contribution of the proposed PRCBGWO technique is described as follows,

- To improve the data packet delivery, the PRCBGWO technique selects the reliable route path from source to destination through the neighboring nodes. In contrast to the existing technique, the PRCBGWO technique uses the probit regression function for analyzing the vehicle node characteristics such as signal strength, distance, and angle of direction. Then the regression function finds the location of the neighboring nodes between the source and destination with better link quality for data transmission resulting in minimizes the end to end delay.

- To improve the throughput, the bio-inspired optimization technique called multi-objective chaotic grey wolf algorithm is introduced. The optimization technique starts with a population of route paths between the source and destination. The path has higher fitness is selected as an optimal based on minimum distance and maximum bandwidth availability for data packet transmission. The maximum bandwidth availability of the path minimizes the packet loss rate and improves the data transmission in IoV.

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RELATED WORK

The community aware mechanism on the Internet of vehicles (CIoVs) [1] was introduced for long-distance communication to propagate the data between the vehicles with minimum delay. But the packet delivery ratio was not improved because it failed to identify the neighboring location. A quality of service-aware routing algorithm (QRA) [2] was designed using a modified laying chicken optimization technique to forwards the packets by discovering the most optimal and connected path. The designed algorithm failed to improve reliable data transmission among the vehicles. Ant Colony Optimized Ad-Hoc On-Demand Distance Vector (ACO-AODV) routing protocol [3] was designed. The designed ACO-AODV algorithm failed to find a global optimum with lesser time complexity. A Moth Fame Clustering Algorithm [4] was developed for IoV robust transmission. The reliability of data transmission was not improved using designed clustering algorithm. Ant colony optimization algorithm [4] was introduced with the Internet of Vehicles based route selection. The algorithm failed to consider the multiple objective functions for solving the optimization issues. An infrastructure-assisted hybrid road-aware routing protocol [5] was designed for improving the data communication with minimum delay. The designed protocol failed to minimize the performance of loss in data communication. The decision tree based vehicle state prediction [6] was presented for reliable communication between the vehicles. But the performance of the data delivery remained unaddressed. A cluster-based optimization framework [7] was introduced for large-scale IoV systems to minimize the transmission delay of communication. The designed framework failed to provide robust performance in terms of packet delivery ratio and delay. A fuzzy logic with ant colony optimization[8] based approach was introduced for optimal gateway selection to perform data transmission. The approach failed to minimize the end to end delay. A social vehicle route selection (SVRS) algorithm [9] was developed to select the optimized route for vehicles communication. But the reliable route path was not selected for improving the data delivery. A cross-layer protocol was proposed [10] for improving the throughput and minimizing the delay. A Swarm Intelligence (SI)-based algorithm called ACO was designed [11] for providing communication among the connected vehicles by identifying the shortest route path. The designed algorithm was not successfully selected global optimal route path to enhance the routing performance. An IoT-enabled dynamic optimization technique was introduced in [12] for vehicles to improve data transmission. However, it failed to focus the global optimization for sharing the information between the network An efficient order-aware hybrid genetic algorithm was proposed [13] for solving the vehicle routing problems. But the performance of the routing metrics such as delivery ratio remained unaddressed. Modified Ant Colony Optimizer was developed [14] for efficient communication with high delivery ratio and minimum delay. The designed technique failed to consider the multiple objective functions to solve the optimization problem. A weighted and undirected graph method[15] was introduced for IoV sensing networks to improve the efficiency of traffic information collection. The method failed to achieve improved transmission performance. A content accessibility preference (CAP) method [16] was proposed for vehicle selection to perform data communication with higher throughput and minimum delay. The performance of packet loss was not minimized. A Group Acknowledgment Strategy (GAS)[17] algorithm was designed for increasing the transmission efficiency with minimum delay and packet loss. But reliable data transmission was not performed. Bayesian nonparametric learning method was proposed [18] for information exchanging and content sharing between the vehicles. The method failed to perform the multi-hop vehicle to vehicle communicationA data content based vehicle clustering technique was designed[19] for enhancing vehicle communication. Though the designed technique minimizes the delay and packet loss, the throughput was not improved. A link reliability-based clustering algorithm (LRCA) was prposed [20] to provide efficient and reliable data communication by choosing stable neighbor vehicles. The designed algorithm failed to minimize the end-to-end delay. The major issues identified from the existing literature are overcome by introducing a new technique called PRCBGWO. The process of PRCBGWO technique is presented in the next section.

3. METHODOLOGY

IoT facilitates the vehicles to communicate with one another and generates a large network where the vehicles act as network nodes. Every vehicle in VANET is free to move in various directions. Due to the dynamic nature of the vehicle, the source node difficult to find the position of the neighboring vehicle to transmit the data packet to destination resulting in increases the delay. In addition, the links between the vehicles are the other major concern due to lack of infrastructure, highly dynamic network topology of wireless links. The link breakage causes an impact on the overall performance and it leads to packet loss. Hence, there is a need for reliable path selection to improve data delivery without route breakage. Hence, there is a need for reliable path selection to improve data delivery without route breakage. The existing IDCIoV was developed for location identification using IRNS and optimal path identification using acyclic tree transformation. The designed IDCIoV failed to consider the characteristics of the vehicle nodes for finding the location of neighbors from source to destination. During data transfer,the end to end delay between the vehicle and road side unit was not minimized. The existing issues are overcome by applying the technique Probit Regressive Chaotic Bio-inspired Grey Wolf Optimization (PRCBGWO). On the contrary to existing IDCIoV, the PRCBGWO technique uses the probit regression function for finding the location of the neighboring node. Regression is the machine learning technique effectively identifies the neighboring location from source to destination with the help of vehicle node characteristics such as distance between the nodes, signal strength, and direction towards the source node. In addition, multi-objective chaotic grey wolf optimization is applied to find the optimal route path between source and destination. The optimization technique is used to find the "best" among the populations with a set of constraints. This includes maximum bandwidth availability and minimum distance.

3.1 System model

The VANET is organized in an undirected graph '$G(v,e)$ where 'v represents vehicle nodes $v_1, v_2, v_3, \ldots . v_n$ distributed over a square area of '$n * n$' within the transmission range 'T_r in the network. 'e' denotes link connecting each pair of nodes. The source vehicle (SV) transmits the data packets to the destination vehicle (DV) through the neighboring nodes $Nn_1, Nn_2, Nn_3,, \ldots . Nn_n$. Before the data transmission, the location of the neighboring nodes is identified. Followed by, the optimal route path (P_{th}) is identified to perform reliable data transmission in IoV. Based on this system model, the proposed PRCBGWO technique is designed and explained in the following sections.

3.2 Probit Regressive Chaotic Bio-inspired Grey Wolf Optimization

The PRCBGWO technique is introduced in IoV inorder to improve reliable data delivery with minimum delay. Due to dynamic network topology, the positions of every participating vehicle are discovered by GPS receiver installed on every vehicle. The PRCBGWO technique is used for optimal route path selection among the available paths to improve the routing performance by selecting the neighboring nodes. The architecture of the PRCBGWO technique is shown in figure 2.

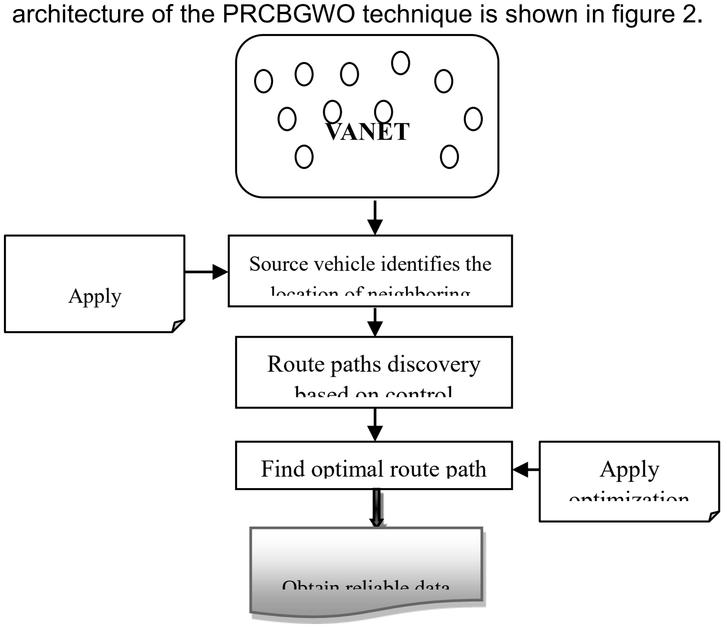

***Figure 2** Flow process of PRCBGWO technique*

Figure 2 shows the flow process of the proposed PRCBGWO technique to improve reliable data delivery in VANET. Initially, the vehicle nodes are distributed randomly in the network. The proposed PRCBGWO technique comprises of two major processes such as neighboring node identification and optimal route path identification. The neighboring node identification is carried out using probit regression. With the help of neighboring nodes multiple route paths are established . Finally, the reliable route among the multiple paths is selected by applying the Multi-Objective Chaotic Grey Wolf Optimization techniques. Then the source vehicle sends the data packets to destination along the route path and obtains reliability in terms of higher data delivery and minimum loss. The detailed explanation of the proposed PRCBGWO technique is described in the following subsections.

Probit regression-based neighboring node location identification

The proposed PRCBGWO technique initially identifies the location of the neighboring nodes to forward the data packets from source to destination. The location of the vehicles nodes in a wireless ad-hoc network is highly significant in VANET. Therefore the proposed PRCBGWO technique uses the Probit regression model to identify the location of the neighboring node in the given dimensional space. Probit regression is the machine learning technique which analyzes the node characteristics and finds the location. Let us consider the number of vehicle nodes $v_1, v_2, v_3, \ldots . v_n$ and defines the source vehicle (SV) and destination vehicle (DV). In order to find the route path between the source and destination vehicle, the location of neighboring node discovery is important for data transmission. The neighboring node location is identified using three characteristics such as distance, signal strength, angle of direction. The coordinates of the source vehicle node is (u_1, v_1) and the coordinate of another vehicle node is (u_2, v_2) in the two dimensional space. Then the Euclidean distance between these nodes is calculated using the following equation.

$$d = \sqrt{(u_i - v_i)^2} \quad (1)$$

In (1), d represents the distance between the two nodes. After discovering the distance measure, the received signal strength is calculated for every node.

$$R_{ss} = 10 \, log_{10} \left(\frac{P_T}{P_R}\right) \quad (2)$$

In (2), R_{ss} denotes a received signal power of the node, P_T denotes a measured power, P_R is the reference power. The coordinate of the source vehicle node is denotes as (u_1, v_1) and the another vehicle node is (u_2, v_2) then the direction of a node from the source vehicle is calculated as follows,

$$tan \, \alpha = \left(\frac{u_2 - u_1}{v_2 - v_1}\right) \quad (3)$$

$$\alpha = \tan^{-1}\left(\frac{u_2 - u_1}{v_2 - v_1}\right) \quad (4)$$

In (3), (4), α denotes an angle between the two vehicles is used for finding the direction of the vehicle node from the source. Then the calculated distance, signal strength and direction information are given to the input of the regression function.

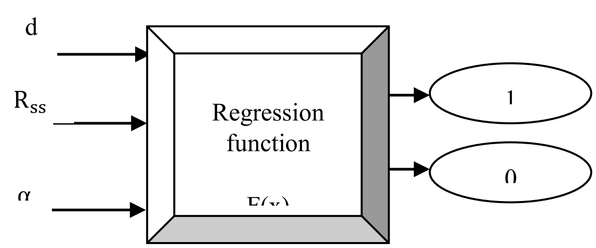

***Figure 3** probit regression-based neighboring node identification*

Figure 3 shows the probit regression to identify the neighboring node in IoV. The regression function analyzes the informations of the nodes such as distance between the nodes, received signal strength and direction.

$$F(x) = d_i < d_j \;\&\&\; R_{ssi} < R_{ssj} \;\&\&\; \alpha 1 \& \alpha 2 = 0 \quad (5)$$

In (5), $F(x)$ denotes a regression function which identifies the neighboring location based on the comparison. If regression function returns the output as '1' (i.e. select neighboring node), the following three conditions are satisfied. Otherwise, it returns '0'.

- when the node 'i' is located with a minimum distance from the source than the node 'j'
- when the node 'i' has maximum received signal strength than the node 'j'
- when the node movement is similar to the direction of the source node

The outcome '1' (select neighboring node with better link quality) or '0' (neighboring node with poor link quality). Based on the above results, the source vehicle find its one-hop neighboring location. The one-hop neighbor finds another one-hop neighboring node based on the regression analysis. Similarly, the locations of the neighboring nodes are identified in IoV. After selecting the neighboring nodes, the route paths from the source to destination are established through the two control message distributions such as route request(req) and reply(rep). Initially, the source vehicle transmits a route request to the selected neighboring nodes.

$$SV \xrightarrow{req} Nn_i \xrightarrow{req} DV \quad (6)$$

From (6), SV denotes a source vehicle, Nn_i denotes selected neighboring nodes, DV represents the destination vehicle. After receiving the request, the neighboring nodes send the reply message back to the source vehicle

$$DV \xrightarrow{rep} Nn_i \xrightarrow{rep} SV \quad (7)$$

By distributing the two control messages, the route paths are established from source to destination vehicle. Among the available route paths, the optimal one is selected for reliable data transmission. The route paths between the source and destination are shown in figure 4.

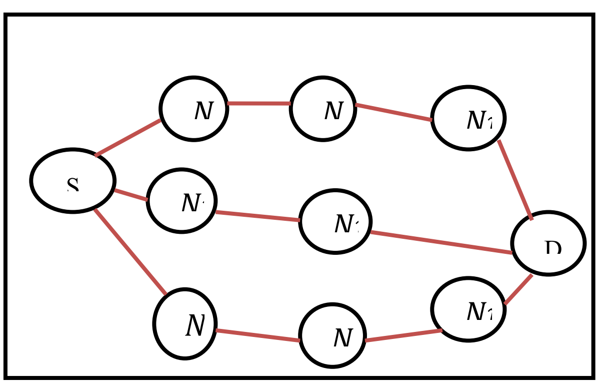

Figure 4 *Route paths construction*

Figure 4 shows the route path construction from source vehicle (SV) to the destination (DV) through the neighboring Nodes $Nn_1, Nn_2, Nn_3, Nn_4, Nn_5, Nn_6, Nn_7, Nn_8$. The regression based neighboring node discovery algorithm is described as follows.

Algorithm 1 describes the step by step process of probit regression-based neighboring node discovery. The probit regression analyzes the distance, signal strength and direction angle of vehicle nodes randomly distributed in the network. The regression function correctly identifies neighboring nodes from source to destination vehicle. In this way, the proposed PRCBGWO technique finds the neighboring nodes for data transmission. Then the route paths between the source and destination are established for data transmission in IoV.

Input: Number of vehicle nodes $v_1, v_2, v_3, \ldots. v_n$
Output: Identify the neighboring node location and route paths
Begin
1. for each vehicle node $\boldsymbol{v_i}$
2. calculate distance '$\boldsymbol{d}$'
3. calculate received signal strength 'R_{ss}'
4. calculate direction angle 'α'
5. if ($d_i < d_j \;\&\&\; R_{ssi} < R_{ss\,j} \;\&\&\; Same\ direction$)
6. y returns '1'
7. Identify the neighboring node
8. else
9. y returns '0'
10. end if
11. end for
12. SV sends req to DV through selected neighboring nodes
13. DV sends route reply rep through neighboring nodes
14. Construct route paths between SV and DV
End

Algorithm 1 probit regression-based neighboring node discovery

3.2 Multi-Objective Chaotic Grey Wolf

Optimization based route path discovery (MCGWO)

The proposed PRCBGWO technique uses the Multi-Objective Chaotic Grey Wolf Optimization (MCGWO) to find the optimal route path among the route paths. The MCGWO technique is a bio-inspired optimization technique that stimulates the hunting process of grey wolves in nature. The MCGWO is a Metaheuristic algorithm that provides the optimal solution due to their simplicity and flexibility than the other optimization technique. The conventional optimization techniques sill not always performs well in finding global optima. The MCGWO uses a chaotic map to find the global optimum solution in the search space. The MCGWO technique generates the populations of 'n' grey wolves (i.e. route paths) $\mathrm{p_1, p_2, p_3, \ldots.. p_n}$ are initialized randomly in search space (i.e. network). After the initialization, the fitness is calculated for each path based on the multiple objective functions between the source and destination. In MCGWO, the grey wolves represented as a route path and the prey represents the fitness of the route path. The path which satisfies the fitness is selected as an optimal for data packet transmission. The multiple objective functions are path length and bandwidth availability. The path length is the distance between the source and destination with number of hop counts. Let us consider the two-dimensional space, the coordinate of the source node is (x_1, y_1) and the coordinate of the destination point is (x_2, y_2). Then the distance between these two points is computed as follows,

$$D = \sqrt{(x_2 - x_1)^2 - (y_2 - y_1)^2} \qquad (8)$$

In (8), D represents the overall distance from the source node (SV) and the destination vehicle node (DV). The bandwidth availability of the route path is calculated based on the difference between the total bandwidth and consumed bandwidth. Therefore, the bandwidth availability is calculated as follows,

$$bw_a = bw_{tt} - bw_u \qquad (9)$$

In (9), bw_a represents a bandwidth availability of the route path from source vehicle and destination vehicle, bw_{tt} is the total bandwidth, bw_u denotes an overall consumed bandwidth. Based on the above said parameters, the fitness of the each individual is calculated as follows,

$$f_t = (\min D)\ \&\&\ (bw_a > \delta) \ (10)$$

In (10), f_t denotes a fitness of the each individual (i.e. path), δ represents the threshold for the bandwidth availability. Then the best first three searching agents (i.e. grey wolves) such as α, β, γ are selected based on the fitness among the populations. In order to find the optimal one, the following processes are carried out in the following subsections.

3.1.1 Encircling the prey

A grey wolf has identify the location of prey (i.e., fitness (minimum distance and higher bandwidth availability)) and encircle them. The encircling process of grey wolves are given by,

$$E = |w.x_p(t) - x_g(t)| \ (11)$$
$$x_g(t+1) = |x_g(t) - k.E| \ (12)$$

In (11) (12), E represents the encircling behavior of the grey wolf, $x_p(t)$ denotes a position of the prey, $x_g(t)$ is the current position of the grey wolf, $x_g(t+1)$ is the updated position of the grey wolf, w, k denotes a coefficient vector. On contrary to a conventional grey wolf optimization, the proposed optimization uses the chaotic map value for finding the global optima. These parameters are defined as follows,

$$w = p\,(2 * c_1 - 1) \ (13)$$
$$k = 2c_1 \ (14)$$

In (13), (14), p denotes a component which is linearly decreased from 2 to 0. c_1 denotes a value obtained from the chaotic map in the range from 0 to 1.

3.1.2 Hunting process

In the hunting process, the position of wolves are updated newly based on the distance measure as follows,

$$x_1 = x_\alpha - k.R_\alpha \ (15)$$
$$x_2 = x_\beta - k.R_\beta (16)$$
$$x_3 = x_\gamma - k.R_\gamma \ (17)$$

From (15) (16) (17), x_1, x_2, x_3 denotes a newly updated position of three hunting agents (alpha, beta and gamma), k denotes a coefficient vector, R_α denotes a distance from the current position of other wolves and alpha wolf, R_β denotes a distance from the current position of other wolves and beta and R_γ represents a distance from the current position of other wolves and gamma. After updating the position, the final updated position of the hunting agents are expressed as follows,

$$x(t+1) = \frac{1}{3}\,(x_1 + x_2 + x_3) \ (18)$$

From (18), $x(t+1)$ denotes a final updated position of the best hunting agent. Then the parameters w, k, p are updated and again calculate the fitness using (10). Finally, replace the old one into the newly best fit individual. This process is iterated until the termination condition is met. In this way, the reliable route path which satisfying the fitness criteria is selected as global optimum one.

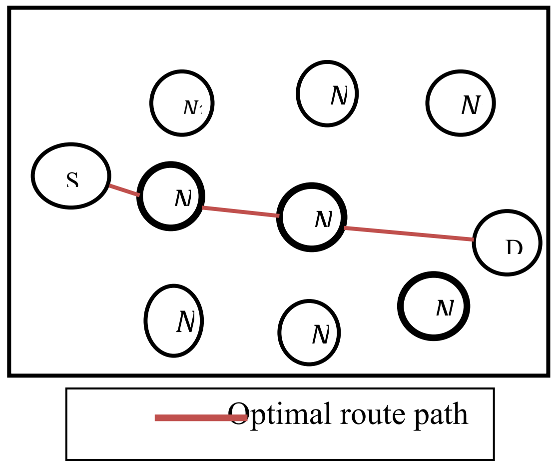

Figure 5 *Multi-Objective Chaotic Grey Wolf Optimization-based path discovery*

Figure 5 shows the optimal path identification from source vehicle to destination through the neighboring nodes. As shown in figure 5, the reliable route path $SV - \mathrm{Nn}_1 - \mathrm{Nn}_4 - \mathrm{DV}$ is selected as optimal for data transmission in IoV. The reliability is achieved by improving data delivery and minimizing the data loss. The algorithm of multi-objective chaotic grey wolf optimization-based route path discovery is described as follows, Algorithm 2 describes the optimization-based route path selection for achieving reliable data delivery from source to destination with minimum loss. The ‘n’ number of paths is considered in search space. Then the fitness of each individual is computed based on the two functions such as distance and bandwidth availability.

Input: Route paths $\mathrm{p}_1, \mathrm{p}_2, \mathrm{p}_3, \ldots.\mathrm{p}_\mathrm{n}$, data packets $Dp_i = Dp_1, Dp_2, Dp_3, \ldots Dp_n$
Output: Optimal route path discovery
Begin
1. Initialize the population of route paths $\mathrm{p}_1, \mathrm{p}_2, \mathrm{p}_3, \ldots.\mathrm{p}_\mathrm{n}$
2. For each route path p_i
3. Calculate distance D and bandwidth availability bw_a
4. Measure the fitness f_t
5. Select best three searching agents α, β, γ based on f_t
6. While (t < maximum iteration)
7. for each searching agent
8. update the position $x_g(t+1)$ with the chaotic sequence map
9. update the position of all searching agents $x(t+1)$
10. update the parameters w, k, p
11. Compute fitness f_t
12. Replace the worst fit wolf with the best fit wolf
13. t=t+1
14. end for
15. end while
16. Return optimal 'α'
17. end for
18. SV sends Dp_i along optimal route path

End

Algorithm 2 Multi-Objective Chaotic Grey Wolf Optimization-based route path selection

Based on fitness, the best three current individuals are selected. The position of the current best individuals gets updated. Then the positions of the searching agents are updated along with the other individuals. Then the fitness of search agents is again recalculated. This process gets repeated until the maximum iteration is reached. By this way, the optimal route path is selected for data transmission. Then the source node sends the data packet to destination along the route path resulting in improves the data delivery.

4 SIMULATION SETUP AND PARAMETER SETTINGS

The simulation of the proposed PRCBGWO technique and existing methods are the quality of service-aware routing algorithm CIoVS [1], QRA [2], ACO-AODV [3], IDCIoV are implemented using NS2.34 network simulator. are implemented using NS2.34 network simulator. Totally 500 vehicle nodes are distributed in a square area of A^2 (1100 m * 1100 m). For the simulation purposes, the Random Waypoint mobility model is used. The simulation time is set as 300 sec. The DSR protocol is used to perform routing and reliable data delivery in VANET. The simulation parameters and the values are shown in table1.

Simulation Parameters	Values
Network Simulator	NS2.34
Square area	1100 m * 1100 m
Number of vehicle nodes	50,100,150,200,250,300,350,400,450,500
Number of data packets	30,60,90,120,150,180,210,240,270,300
Size of data packet	10KB-100KB
Mobility model	Random Waypoint model
Speed of nodes	0 – 20 m/s
Simulation time	300sec
Protocol	DSR
Number of runs	10

***Table 1** Simulation parameters settings*

4. RESULTS AND DISCUSSION

The simulation results of PRCBGWO technique and existing methods CIoVS [1], QRA [2], ACO-AODV [3], IDCIoV are discussed in this section with different parameters such as packet delivery ratio, packet loss rate, end to end delay and throughput with respect to a number of data packets. The simulation results are described with the help of table and graphical representation. For each subsection, the sample mathematical calculation is provided to show the performance of the proposed technique and existing methods.

5.1Simulation analysis of packet delivery ratio

Packet delivery ratio is measured as the ratio of a number of data packets received at the destination to the total number of packets sent from the source node. The formula for calculating the packet delivery ratio is mathematically calculated as follows,

$$PDR = \left(\frac{Number\ of\ data\ packets\ received}{Number\ of\ data\ packet\ sent}\right) * 100 \quad (19)$$

In (19),PDR represents the packet delivery ratio measured in terms of percentage (%).

Number of data packets	Packet delivery ratio (%)				
	PRCBG WO	IDCIo V	CIoVS	QRA	ACO-AODV
30	83	80	70	77	73
60	87	83	75	80	77
90	88	84	76	81	78
120	91	86	80	83	82
150	92	87	81	84	83
180	93	89	83	86	84
210	94	90	84	88	86
240	95	91	85	89	87
270	96	92	87	90	89
300	97	93	88	91	90

***Table 2** Packet delivery ratio versus number of data packets*

Table 2 shows the simulation results of the packet delivery ratio versus a number of data packets in the range from 30 to

300. The simulation results of the PRCBGWO technique and IDCIoV, CIoVS[1], QRA [2] and ACO-AODV [3] are shown in the table 2. The ten different results show that the PRCBGWO technique enhances the packet delivery ratio than conventional techniques. In this case, the source node sends 30 data packets and 25 data packets are received at the destination using the PRCBGWO technique. Therefore the percentage of packet delivery ratio is 83%. While sending the 30 data packets, 24, 21, 23, and 22 data packets are received and the packet delivery ratio is 80%,70 %, 77% and 73% using IDCIoV, CIoVS[1], QRA [2] and ACO-AODV [3] respectively. The different results of the packet delivery ratio are shown in figure 6.

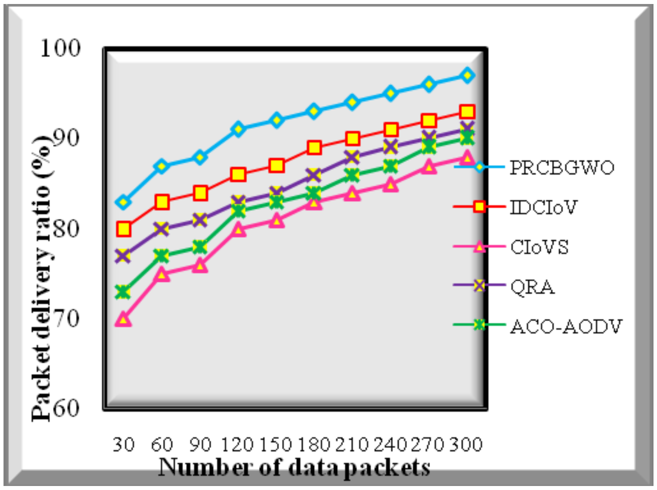

Figure 6 *Graphical representation of packet delivery ratio*

Figure 6 depicts the performance results of the packet delivery ratio versus a number of data packets. As shown in the figure, the number of data packets is taken as input in the 'x' axis and the results of the packet delivery ratio are obtained at the 'y' axis. The graphical results show that the packet delivery ratio of three different techniques PRCBGWO technique and IDCIoV, CIoVS[1] , QRA [2] and ACO-AODV [3] are represented in three different colors such as violet, red and green respectively. The observed results clearly show that the packet delivery ratio is found to be higher using the PRCBGWO technique than the other two optimization techniques. This significant improvement is achieved by performing the regression based optimal route path discovery. The conventional technique did not use any machine learning techniques for neighboring node selection. On the contrary, the proposed PRCBGWO technique uses the probit regression to find the neighboring node by analyzing the distance, signal strength and direction towards the destination node. With the selected node, the optimal route path is identified among the available paths using chaotic grey wolves' optimization with the multiple objective functions such as distance and bandwidth availability. The path with minimum distance and higher bandwidth availability is chosen as an optimal one for data packet transmission. This helps to improve the data packet delivery. The ten different simulation results of the PRCBGWO technique is compared to the packet delivery ratio of the IDCIoV, CIoVS[1] , QRA [2] and ACO-AODV [3]. The average of packet delivery ratio is increased by 5%, 13%, 8% and 11% using the PRCBGWO technique as compared to existing techniques.

5.2 Simulation analysis of packet loss rate

The packet loss rate is measured as the ratio of a number of data packets lost to the total number of packets sent from the source node. The packet loss rate is mathematically calculated as follows,

$$PLR = \left(\frac{Number\ of\ data\ packets\ loss}{Number\ of\ data\ packet\ sent}\right) * 100 \quad (20)$$

In (20),PLR represents the packet loss rate measured in terms of percentage (%).

Table 3 *Packet loss rate versus number of data packets*

Number of data packets	End to end delay (ms)				
	PRCB GWO	IDCIoV	CIoVS	QRA	ACO-AODV
30	18	20	26	22	24
60	25	27	35	30	32
90	28	30	36	32	34
120	32	35	40	37	38
150	35	38	43	40	41
180	37	40	46	42	44
210	40	42	50	45	48
240	44	46	52	48	50
270	47	50	55	52	53
300	50	52	57	54	55

To estimate the packet loss rate, the numbers of data packets are taken as input in the range of 30-300. While considering the 30 data packets to perform the simulation process, PRCBGWO technique lost 5 data packets and their loss percentage is 17% and the loss percentage of the IDCIoV, CIoVS[1], QRA [2] and ACO-AODV [3] are 20%,30%, 23%, and 27% respectively. Similarly, the various results of the packet loss rate are reported in the table. The graphical results of the packet loss rate are shown below.

Number of data packets	Packet loss rate (%)				
	PRCBG WO	IDCIoV	CIoVS	QRA	ACO-AODV
30	17	20	30	23	27
60	13	17	25	20	23
90	12	16	24	19	22
120	9	14	20	17	18
150	8	13	19	16	17
180	7	11	17	14	16
210	6	10	16	12	14
240	5	9	15	11	13
270	4	8	13	10	11
300	3	7	12	9	10

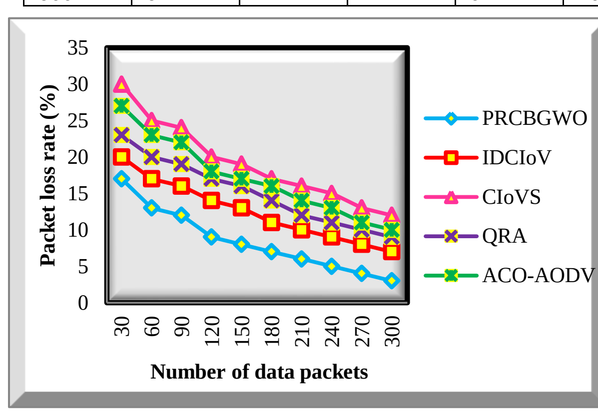

Figure 7 *Graphical representation of packet loss rate*

Figure 7 depicts the rate of packet loss of three different methods namely PRCBGWO technique, IDCIoV, CIoVS[1], QRA [2] and ACO-AODV [3] with respect to a different number of data packets. The above graphical results show that the packet loss rate is considerably minimized than the existing techniques. This is because of the application of Multi-Objective Chaotic Grey Wolf Optimization. The optimization technique considers the bandwidth availability of the route paths for data packet transmission. The lowest bandwidth availability causes the congestion resulting causes the more packet drop. In order to solve this problem, the packet loss is minimized by selecting the optimal route path with maximum bandwidth availability. In addition, the minimum distance and less number of hop counts between the source and destination are selected for minimizing the packet loss using PRCBGWO technique. The simulation result of the proposed technique is evaluated with the existing technique. The average of ten results of the packet loss rate is found to be minimized using the PRCBGWO technique by 37%, 59%, 47% and 54% as compared to IDCIoV, CIoVS[1], QRA [2] and ACO-AODV [3]. This result shows that PRCBGWO technique method has an ability to improve the reliability in terms of minimum packet loss.

5 SIMULATION ANALYSIS OF END TO END DELAY

End to end delay is measured as the difference between the data packet arrival time and sending time. The end to end delay is mathematically calculated using the following formula,

$$EED = (Dp_{Arr} - Dp_s) \qquad (21)$$

From equation (21), EED denotes an end to end delay, Dp_{Arr} represents the data packet arrival time, Dp_s denotes a data packet sending time.

Table 4 End to end delay versus the number of data packets
The simulation results of end to end delay versus a number of data packets using five different techniques PRCBGWO, IDCIoV, CIoVS[1], QRA [2] and ACO-AODV [3] is described in table 4. The delay is measured as the amount of time delay to receive the data packet at the destination end in IoV. The comparison results of three techniques with various end to end delays are shown in the graph.

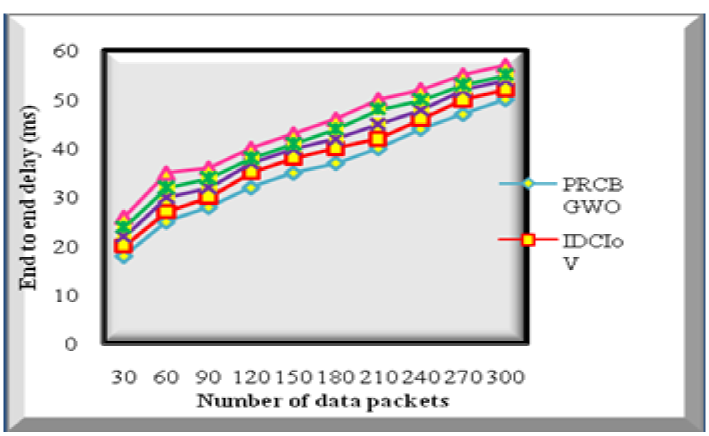

Figure 8 *Graphical representation of end to end delay*

Figure 8 given above shows the plot of end to end delay with respect to a different number of data packets. Here, the end to end delay refers to the time-delayed for receiving the data packets. With the increase in the number of data packets the delay for data delivery also increases. Also, a linear increase is found to be observed. Besides, from the sample calculation provided above the table, with '30' data packets are considered, the delay for data delivery using PRCBGWO technique was found to be '$18ms$' and delay of IDCIoV, CIoVS[1] , QRA [2] and ACO-AODV [3] was found to be '$20ms$', $26ms$', $22ms$' and '$24ms$' respectively. From the sample calculations, it is inferred that the overall end to end delay is minimized by applying the PRCBGWO technique. This is because by applying regression based neighboring selection and optimization techniques. The signal strength, distance, and direction of the node are selected as neighbors for data packet transmission. In addition, the optimal route path with less number of hop counts are selected to transmit the data packets from source to destination resulting it minimizes the delay. As a result, the comparison results show that the end to end delay of the PRCBGWO technique is significantly minimized by 7%, 20%, 12% and 16% than the IDCIoV, CIoVS[1] , QRA [2] and ACO-AODV [3] respectively.

5.1 Simulation results of throughput

The throughput is measured as an amount of data delivered from source to destination in a given period of time. The mathematical formula for calculating the throughput is given by.

$$Throughput = \frac{Amount\ of\ Dp\ received\ (bits)}{time\ (second)} \qquad (22)$$

In (22), Dp denotes a data packet, throughput is measured in terms of bits per second (bps).

Data packet size (KB)	Throughput (bps)				
	PRCBGWO	IDCIoV	CIoVS	QRA	ACO-AODV
10	142	135	105	128	110
20	250	220	130	180	146
30	342	310	195	280	220
40	463	430	310	405	350
50	543	510	410	480	450
60	675	620	500	580	530
70	741	700	580	650	620
80	812	760	620	720	670
90	974	890	730	810	770
100	1120	1056	840	980	880

Table 5 *Throughput versus size of data packets*

Table 5 shows the simulation results of throughput versus the size of the data packet being sent from the source vehicle to the destination. The various throughput results are obtained while varying the data packets size. The above-reported results show that the PRCBGWO technique increases the throughput than the state-of-the-art methods.

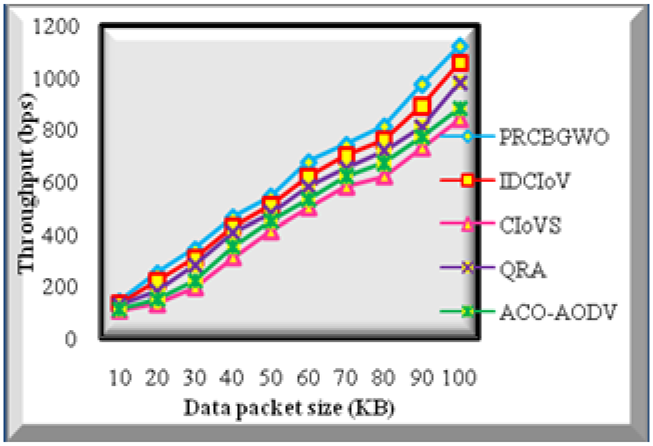

Figure 9 *Graphical representation of Throughput*

Figure 9 depicts the graphical representation of throughput versus data packet size being sent from 10KB to 100KB. As shown in the above graphical results, the PRCBGWO technique achieves higher network throughput while sending the data packet from source to destination. This is because the PRCBGWO technique selects the optimal route between the vehicle nodes and also selects the neighboring nodes present between the source and destination node. This helps to minimize the unwanted traffic congestion while routing the data packets which leads to enhancement in network throughput. Higher the network throughput achieves less transmission overhead in the VANET. The reported results show that the throughput of the PRCBGWO technique is considerably improved by 8%, 45%, 18% and 33% as compared to IDCIoV, CIoVS[1], QRA [2], ACO-AODV [3] respectively. The discussed results clearly show that the PRCBGWO technique achieves reliable data transmission by achieving the higher packet delivery ratio, throughput, and minimum delay as well as packet loss.

CONCLUSION

An efficient PRCBGWO technique is developed with the aim of improving reliable data delivery in IoV by identifying the neighboring node and route path. The source node initially finds the location of the neighboring nodes with help of regression analyzes using received signal strength, distance, and direction. The several route paths are established between the nodes to identify the optimal route path. Finally, the optimum path is identified by applying the chaotic grey wolf optimization with multiple objective functions. Then the reliable data transmission is performed along the optimal route path in order to achieve higher delivery ratio and minimum packet loss. Simulation is carried out with different performance metrics such as packet delivery ratio, packet loss rate, end to end delay and throughput with respect to a number of data packets. The performance results confirm that PRCBGWO technique improves the path reliability in terms of high packet delivery ratio, throughput and a minimum end to end delay as well as packet loss than the state-of-the-art methods.

REFERENCES

[1] Tie Qiu,Xize Liu, Keqiu Li, Qing Hu, Arun Kumar Sangaiah, Ning Chen, "Community-Aware Data Propagation with Small World Feature for the Internet of Vehicles", IEEE Communications Magazine, Volume 56, Issue 1, 2018, Pages 86 – 91

[2] Kayhan Zrar Ghafoor , Linghe Kong , Danda B. Rawat , Eghbal Hosseini , Ali Safaa Sadiq, "Quality of Service Aware Routing Protocol in Software-Defined Internet of Vehicles" , IEEE Internet of Things Journal , Volume 6 , Issue 2 , 2019, Pages 2817 – 2828

[3] Mahadev A. Gawas and Sweta S. Govekar, "A novel selective cross layer based routing scheme using ACO method for vehicular networks", Journal of Network and Computer Applications, Elsevier, Volume 143, 2019, Pages 34-46

[4] Muhammad Fahad Khan , Farhan Aadil , Muazzam Maqsood , Syed Hashim Raza Bukhari , Maqbool Hussain, and Yunyoung Nam , "Moth Flame Clustering Algorithm for Internet of Vehicle (MFCA-IoV)", IEEE Access , Volume 7, Pages 11613 – 11629

[5] Priyan Malarvizhi Kumar , Usha Devi G , Gunasekaran Manogaran , Revathi Sundarasekar , Naveen Chilamkurti , R. Varatharajan, "Ant colony optimization algorithm with Internet of Vehicles for Intelligent TrafÞc Control System", Computer Networks, Elsevier, Volume 144, 2018, Pages 154-162

[6] Muhammad Tahir Abbas, Afaq Muhammad, Wang-Cheol Song, "Road-Aware Estimation Model for Path Duration in Internet of Vehicles (IoV)", Wireless Personal Communications, Springer, 2019, Pages 1–24 Yanting Liu , Ding Cheng , Yirui Wang , Jiujun Cheng , and Shangce Gao, "A Novel Method for Predicting Vehicle State in Internet of Vehicles", Mobile Information Systems, Hindawi, Volume 2018, May 2018, Pages 1-13

[7] Xiaojie Wang, Zhaolong Ning, Xiping Hu , Lei Wang , Bin Hu , Jun Cheng, Victor C. M. Leung, "Optimizing Content Dissemination for Real-Time Traffic Management in Large-Scale Internet of Vehicle Systems", IEEE Transactions on Vehicular Technology , Volume 68 , Issue 2 2019, Pages 1093 – 1105

[8] Issam Jabri, Tesnim Mekki, Abderrezak Rachedi, Maher Ben Jemaa, "Vehicular fog gateways selection on the internet of vehicles: A fuzzy logic with ant colony optimization based approach", Ad Hoc Networks, Elsevier, Volume 91, 2019, Pages 1-16

[9] Kai Lin , Chensi Li, Giancarlo Fortino, Joel J. P. C. Rodrigues, "Vehicle Route Selection Based on Game Evolution in Social Internet of Vehicles", IEEE Internet of Things Journal , Volume 5 , Issue 4 , 2018, Pages 2423 – 2430

[10] Bindiya Jain, Gursewak Brar, Jyoteesh Malhotra, Shalli Rani, and Syed Hassan Ahmed, "A cross layer protocol for traffic management in social internet of vehicles," Future Generation Computer Systems, Elsevier, Volume 82, 2018, Pages 707-717 Khac-Hoai Nam Bui and Jason J. Jung, "ACO-based Dynamic Decision Making for Connected Vehicles in IoT System", IEEE Transactions on Industrial Informatics, 2019, Pages 1-8

[11] Sichao Liu, Yingfeng Zhang, Yang Liu, Lihui Wang, Xi Vincent Wang, "An 'Internet of Things' enabled dynamic optimization method for smart vehicles and logistics tasks", Journal of Cleaner Production, Elsevier, Volume 215, 2019, Pages 806-820

[12] Na Lin , Yanjun Shi, Tongliang Zhang , Xuping Wang, "An Effective Order-Aware Hybrid Genetic Algorithm for

Capacitated Vehicle Routing Problems in Internet of Things", IEEE Access, Volume 7 , Pages 86102 – 86114
[13] Sahar Ebadinezhad , Ziya Dereboylu and Enver Ever, "Clustering-Based Modified Ant Colony Optimizer for Internet of Vehicles (CACOIOV)", Sustainability, Volume 11, Issue 9, 2019, Pages 1-22
[14] Jingjing Wang , Chunxiao Jiang , Zhu Han , Yong Ren , Lajos Hanzo, "Internet of Vehicles: Sensing-Aided Transportation Information Collection and Diffusion", IEEE Transactions on Vehicular Technology , Volume 67 , Issue 5 , 2018, Pages 3813 – 3825
[15] Amr Tolba, "Content accessibility preference approach for improving service optimality in internet of vehicles", Computer Networks, Elsevier, Volume 152, 2019, Pages 78-86
[16] Chen Chen, Tingting Xiao, Honghui Zhao, Lei Liu, Qingqi Pei, "GAS: A group acknowledgment strategy for popular content distribution in Internet of vehicle", Vehicular Communications, Elsevier, Volume 17, 2019, Pages 35–49
[17] Zhenyu Zhou , Caixia Gao , Chen Xu , Yan Zhang , Shahid Mumtaz , Jonathan Rodriguez, "Social Big-Data-Based Content Dissemination in Internet of Vehicles", IEEE Transactions on Industrial Informatics , Volume 14 , Issue 2 , 2018, Pages 768 - 777
[18] Kai Lin, Fuzhen Xia, Giancarlo Fortino, "Data-driven clustering for multimedia communication in Internet of vehicles", Future Generation Computer Systems, Elsevier, Volume 94, 2019, Pages 610-619
[19] Xiang Ji , Huiqun Yu, Guisheng Fan , Huaiying Sun, and Liqiong Chen, "Efficient and Reliable Cluster-Based Data Transmission for Vehicular Ad Hoc Networks", Mobile Information Systems, Hindawi, Volume 2018, July 2018, Pages 1-15