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DFQIoV: Design of a Dynamic Fan-Shaped-Clustering Model for QoS-aware Routing in IoV Networks

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Abstract— Internet of Vehicles (IoV) is a steadily growing field of research that deals with highly ad-hoc wireless networks. These networks require design of high-speed & high-efficiency routing models, that can be applied to dynamically changing network scenarios. Existing models that perform this task are highly complex and require larger delays for estimation of dynamic routes. While, models that have faster performance, do not consider comprehensive parameters, which limits their applicability when used for large-scale network scenarios. To overcome these limitations, this text proposes design of a novel dynamic fan-shaped clustering model for QoS-aware routing in IoV networks. The model initially collects network information sets including node positions, & energy levels, and combines them with their temporal packet delivery & throughput performance levels. These aggregated information sets are processed via a hybrid bioinspired fan shaped clustering model, that aims at optimization of routing performance via deployment of dynamic clustering process. The model performs destination-aware routing process which assists in reducing communication redundances. This is done via a combination of Elephant Herding Optimization (EHO) with Particle Swarm Optimization (PSO), which integrates continuous learning for router level operations. The integrated model is able to reduce communication delays by 5.9%, while improving energy efficiency by 8.3%, throughput by 4.5%, and packet delivery performance by 1.4% under different network scenarios. Due to which the proposed model is capable of deployment for a wide variety of dynamic network scenarios.

Keywords- Routing, Particle Swarm Optimization, Elephant Herding Optimization, Delay, Energy, Throughput, Packet Ratio.

I. INTRODUCTION

IoV based routing protocol design requires integration of multimodal frameworks that can analyse dynamic network configurations. These frameworks must include analysis of node-level topologies, network structure, dynamically changing node behaviour, Quality of Service (QoS), etc. A typical IoV routing model [1] is depicted in Fig. 1, wherein cluster formation is followed by collaborative gateway identification for efficient route optimizations. The proposed model initially collects data from base-station & other vehicular nodes and use it for density-based clustering operations. The formed clusters are used for identification of

recording angles, which assists in estimation of Global Queuing Index (GQI) using the evaluation function, GQI=f(E,d,P,T) Where, E,d,P & T reflects the energy levels, distance metrics, packet delivery ratio, and throughput levels of the node sets, whilst f represents the evaluation function for estimate of the GQI levels. The value of the GQI is used to generate a list of plausible routing nodes, which helps in the discovery of QoS-aware routes. This procedure is carried performed several times for a variety of routing requests, which contributes to the ongoing discovery of routing configurations. This model, however, is dependent on the collaborative information provided by other nodes. As a result, the latency associated with route estimate rises, which in turn reduces the model's scalability for use in large-scale network situations.

The next portion of this article provides an overview of comparable models [2, 3, 4], during which their operational subtleties, deployment-specific benefits, application-specific restrictions, and deployment-specific future scopes are dissected in depth. After having this conversation, it was established that the present models for carrying out this activity are exceedingly complicated, which results in the need of lengthier estimating durations for dynamic routes. Although models with better performance do not take into account all of the relevant characteristics, their usefulness in large-scale network situations is severely limited. To get around these restrictions, a unique dynamic fan-shaped clustering model for QoS-aware routing in IoV networks is presented in section 3 of this paper. This model may be found in this document. In section 4, the performance of this model was tested in terms of routing latency, energy efficiency, packet delivery

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performance, and throughput levels. It was compared to a variety of state-of-the-art approaches throughout this evaluation. This article draws to a close with a number of network-specific observations about the model that has been provided, as well as ideas for additional performance enhancements.

II. LITERATURE REVIEW

A large number of IoV routing models are proposed by researchers, and each of them varies in terms of its internal operating characteristics. For instance, work in [5, 6] proposes use of Traffic Awareness with Link Preference, and Vehicle Position Analysis for estimation of efficient routes. These models are highly complex, and cannot be scaled for multiple network scenarios. To overcome these issues, work in [7] proposes use of Advanced Greedy Hybrid Bio-Inspired Routing that aims at improving route identification performance for multiple use cases. Similar models are discussed in [8, 9, 10], which propose use of temporal convolutional network with reinforcement learning mechanism (TCN RL), Online Sequential Learning-Based Adaptive Routing with Software-Defined Vehicular Networks (OSL AR SDN), and Reinforcement Learning, which aims at iteratively optimizing route selection performance under large scale network scenarios. These models are highly efficient, and can be used for a wide variety of routing use cases. Extensions to these models are discussed in [11, 12, 13], which propose use of Two-Tier Collection and Processing Schemes, Heterogeneous Earliest Finish Time (eHEFT) Model, and multiple learning models for estimation of QoS-aware routes in real-time network scenarios.

Models that use QoS-Aware Grid Routing based on Reinforcement Learning (QGRL) [14], Multi-Lane Connectivity Routing (MLCR) [15], Ant Colony Optimization Ad hoc On-demand Distance Vector (ACO-AODV) [16], Scheduled Routing [17], and information-center networking (ICN) [18] aim at optimizing route selection via integration of low complexity, and high-density feature representation techniques. These models are further extended in [19, 20] via use of Probabilistic Broadcasting Schemes, Self-Assessment Cluster (SAC) Routing, which integrates different learning models for enhancement of route selection performance under multiple traffic types. Similar models are discussed in [21, 22, 23, 24, 25], which propose use of short-range OFDM wideband communication (SOWC), Incentive and Punishment Scheme (IPS), Crowdsensing based routing, Mix Integer Non-Linear Programming (MINLP), and coupling mode (CRF) with decoupling mode (DRF) for estimation of fault-aware routes. But these models are extremely complicated and call for longer delays before providing an estimation of dynamic routes. However, models that have a faster performance do not take into account comprehensive parameters, which restricts their applicability when applied to large-scale network scenarios. To overcome these issues, next section proposes a light-weight dynamic fan-shaped clustering model for QoS-aware routing in IoV networks. The model was evaluated under multiple scenarios, and compared with various state-of-the-art techniques, to estimate its performance, and validate it for real-time use cases.

III. DESIGN OF THE PROPOSED DYNAMIC FAN-SHAPED CLUSTERING MODEL FOR QOS-AWARE ROUTING IN IOV NETWORKS

As a result of reviewing the existing IoV routing models, it has been observed that these models are extremely complicated and call for longer delays before providing an estimation of dynamic routes. However, models that have a faster performance do not take into account comprehensive parameters, which restrict their applicability when applied to large-scale network scenarios.

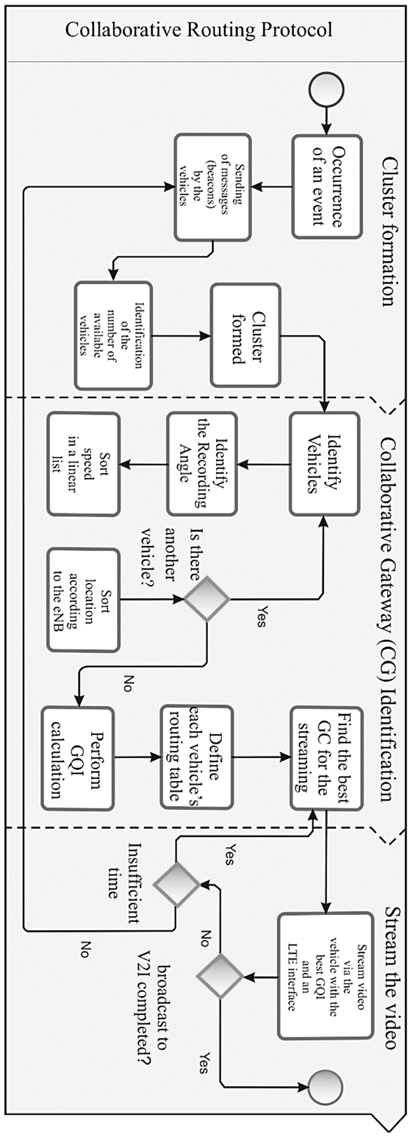

Figure 1. Design of a collaborative IoV routing model for QoS aware operations

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This section proposes the design of a novel dynamic fan-shaped clustering model for QoS-aware routing in IoV networks in an effort to overcome the limitations that have been outlined. The flow of the model is depicted in Fig. 2, where it can be seen that the model initially collects network information sets including node positions and energy levels and combines them with their temporal packet delivery and throughput performance levels. This is shown as the first step in the model's overall process. These compiled data sets are then put through a hybrid bioinspired fan-shaped clustering model for processing. This model's purpose is to maximize the efficiency of the routing process through the utilization of a dynamic clustering procedure. A destination-aware routing process is carried out by the model, which contributes to the reduction of communication redundancies. This is accomplished by integrating continuous learning for router level operations into Elephant Herding Optimization (EHO), which is a combination of Particle Swarm Optimization (PSO) and Elephant Herding Optimization processes.

The model initially clusters nodes based on destination node's location via a Fan Shaped Clustering (FSC) process. This process initially estimates maximum 1-hop distance d_1hop for destination node, and evaluates node cluster level (CL) via equation 1,

$$CL_i = \frac{\sqrt{(x_i - x_{dest})^2 + (y_i - y_{dest})^2}}{d_{1hop}} \qquad (1)$$

Where, x,y represents node locations in Cartesian coordinate system, while i represents current node number for which level is being evaluated to form clusters. Using this approach, the network is divided up into a series of fan-shaped clusters, each of which makes full use of the advantages that come with location-based clustering. The widths of the rings are constantly and evenly fixed in this subdivision, which is indicated by the letter r. The workload will be divided evenly across all of the nodes in the cluster if the cluster sizes are all brought up to the same level. Therefore, the ith level ring is divided into (2i-1) times four subrings, and each of these subrings has an area of its own. The sink would typically be situated in the exact geographic middle of the network in a configuration of this kind. On the other hand, if the sink is situated in a more peripheral location, this barrier might be used in its place. Previous studies often made use of the coverage radius of each node in order to determine the value of a cluster. In other words, the length is designed in such a way that each node may effectively cover not only the clusters that are immediately next to it but also the clusters that are located farther away. In our method, we begin with the assumption of a square cluster length (l), and we get r by determining the greatest distance (distance X-Y) that exists between any two adjacent clusters. It is possible for many values of i to get the same result for ri (ranging from 1 to N). In this instance, we bring r down to its lowest possible value (ri). In the scenario in which i=3, our computation brings us to the conclusion that, where is also the coverage radius of the node. This value of r ensures that there is continuous communication between any two nodes that are in close proximity to one another. Sending a partition message is what kicks off the operation of partitioning, which is started by the sink node. This message includes a variety of pieces of information, including the current value of the parameter r, the location of the sink, the size of the center zone, and more. After getting this message, every node will determine whether or not it is a part of the cluster by using both its own location data and the information sets that it has been given for multiple use cases.

Evaluate cluster level for each node, and then apply an Elephant Herding Particle Swarm Optimizer (EHPSO) Model to evaluate routes. The EHPSO Model is used to improve the speed of decision making, which is not catered by other bio-inspired models. The optimization is performed via the following process,

- To start the optimization process, initially setup following model parameters,
  - Total EHPSO optimization iterations (N_i)
  - Total EHPSO particles (N_p)
  - Total EHPSO herds (N_h)
  - Social & Cognitive learning rates (L_s & L_c)
  - Temporal packet delivery performance and throughput levels for all nodes
  - Node locations and their energy levels
- Initially generate N_h herds via the following process,
  - Select a stochastic node from current cluster that caters equation 2,

$$d_{i,dest} < d_{ref} \ \& \ d_{i,src} < d_{ref} \qquad (2)$$

Where, $d_{i,dest}, d_{i,src}$ & d_{ref} represents distance between current node & destination, distance between current node & source, and direct distance between source & destination nodes. This node selection is done by stochastically selecting a node from the list of nodes that satisfy equation 2, thus indicating nodes that are present in current path between source & destination nodes.

  - Repeat this process for next clusters till source node cluster is reached, and evaluate herd fitness via equation 3, which assists in calculating herd fitness,

$$f = \frac{1}{N_t}\sum_{i=1}^{N_t}\sum_{i=1}^{N_{sel}} \frac{d(sel_j, sel_{j+1})}{d_{ref}} + \frac{Max(E)}{E_j} + \frac{Max(THR)}{THR_j} + \frac{100}{PDR_j} \qquad (3)$$

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Where, d represents node-to-node distance, E represents residual energy levels of nodes, THR represents temporal throughput levels, while PDR represents temporal packet delivery ratio of the nodes when estimated for N_t communications, and N_{sel} represents number of nodes selected between source & destination for routing process.

- Generate such combinations, and then select herd with highest fitness as 'Matriarch' herd.
- Once this is done, then scan all herds for N_i iterations, and update herd fitness via equation 3.1,

$$f(New) = r * f(Old) + L_c * \big(f(Old) - f(Best)\big) + L_s * \big(f(Old) - f(M)\big) \quad (3.1)$$

Where, $f(Best)$ is previous best fitness of the herd, while $f(M)$ represents fitness levels of the 'Matriarch' herd, and $f(New)$ & $f(Old)$ represents new & old fitness levels of the herds.

- If $f(New) > f(Old)$, then do not update fitness levels of the herd, else, stochastically modify $L_c * N_{sel}$ nodes from current herd by referring to 'Matriarch' herd configurations.
- At the end of each iteration, update fitness of all herds, and select 'Matriarch' herd with minimum fitness levels.

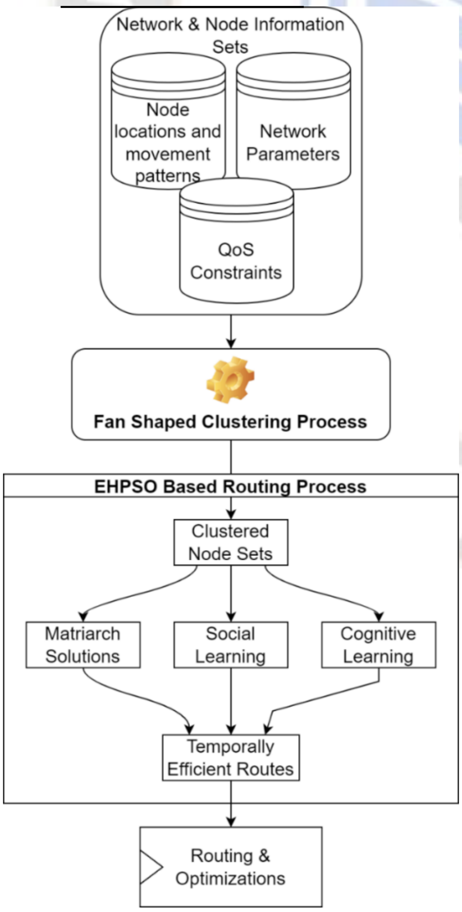

Figure 2. Fan Shaped Clustering with Bio-inspired Optimizations

This process is repeated for N_i iterations, and routing configurations of 'Matriarch' herd are used for routing process. This enables the model to achieve better energy efficiency with lower delay, higher throughput and better packet delivery performance levels. Performance of the model is validated on standard network configurations in the next section of this text.

IV. RESULT ANALYSIS & COMPARISON

The DFQIoV Model that has been proposed utilizes a combination of Fan Shaped Clustering with Elephant Herding Optimization and Particle Swarm Optimization in order to locate fault-tolerant and low complexity routes. These routes have been chosen because they have a low delay, a low energy consumption, a high temporal throughput, and high temporal PDR performance levels. A comparison of the proposed model to the models proposed in TCN RL [8], OSL AR SDN [9], and ACO [16] is going to take place in this section. The following information regarding the network's parameters is used in this comparison,

TABLE I. STANDARD NETWORK PARAMETERS USED DURING THE ROUTING & VALIDATION PROCESS

Network Parameter	Value of the Parameter
Total IoV Nodes	200 to 500
Routing Protocol Model	Ad-hoc On Demand Distance Vector (AODV)
Type of Antennas used for communication	Omnidirectional Antennas
Type of Queue	Priority Queue with Drop-tailing of packets
Dimensions of Network	1 km x 1 km
Transmission energy needed during communications	0.5 mJ
Reception energy needed during communications	0.125 mJ
Sleep energy needed during communications	0.005 mJ
Travel energy needed during communications	2 mJ
Idle energy needed during communications	0.025 mJ

To evaluate communication speed, average delay was evaluated for N different communications via equation 4,

$$D = \frac{1}{N}\sum_{i=1}^{N} t_{end_i} - t_{start_i} \quad (4)$$

Where, t_{start} & t_{end} are the starting communication and finishing communication timestamps. This communication delay was evaluated for N different communication sets, and tabulated in table 2 as follows,

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TABLE II. AVERAGE COMMUNICATION DELAY FOR DIFFERENT IOV ROUTING MODELS

N	D (ms) TCN RL [8]	D (ms) OSL AR SDN [9]	D (ms) ACO [16]	D (ms) DFQ IOV
20	6.80	8.00	5.03	3.94
40	7.15	8.45	5.50	4.19
60	7.50	8.78	6.00	4.42
80	7.82	9.03	6.48	4.63
100	8.27	9.28	6.96	4.87
120	8.66	9.45	7.44	5.08
140	9.17	9.70	7.92	5.33
160	9.64	10.00	8.41	5.58
180	10.04	10.33	8.89	5.82
200	10.46	10.65	9.37	6.06

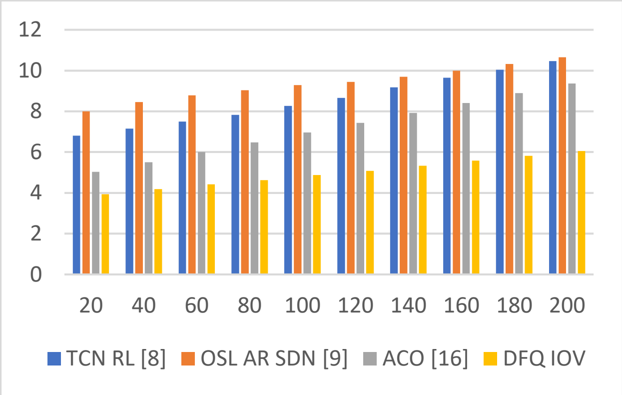

Figure 3. Average communication delay for different IoV routing models

In light of the results of this analysis and the information presented in Fig. 3, it is clear that the proposed model has a delay that is 14.5 percentage points lower in comparison to TCN RL [8], nearly 15.2 percentage points lower in comparison to OSL AR SDN [9], and approximately 10.5 percentage points lower in comparison to ACO [16]. Since of this, it is very helpful for implementing high-speed routing because it cuts down on latency by such a significant amount. The aforementioned increase in routing speed can be traced back to the incorporation of distance measurements into the process of modelling the routing fitness functions as the root cause of the changes. Similarly, energy consumption was evaluated via equation 5, as follows,

$$E = \frac{1}{N}\sum_{i=1}^{N} E_{start_i} - E_{end_i} \tag{5}$$

Where, E_{start} & E_{end} are the initial and final energy levels of nodes while performing communication operations. This energy was evaluated for different number of communications, and tabulated in table 3 as follows,

TABLE III. AVERAGE ENERGY CONSUMPTION FOR DIFFERENT IOV ROUTING MODELS

N	E (mJ) TCN RL [8]	E (mJ) OSL AR SDN [9]	E (mJ) ACO [16]	E (mJ) DFQ IOV
20	8.58	10.97	8.27	5.02
40	8.99	11.41	8.99	5.30
60	9.43	11.77	9.72	5.57
80	9.90	12.06	10.43	5.84
100	10.44	12.36	11.16	6.11
120	10.99	12.67	11.88	6.40
140	11.54	13.06	12.60	6.69
160	12.07	13.45	13.33	6.98
180	12.53	13.83	14.05	7.26
200	12.90	14.40	14.77	7.54

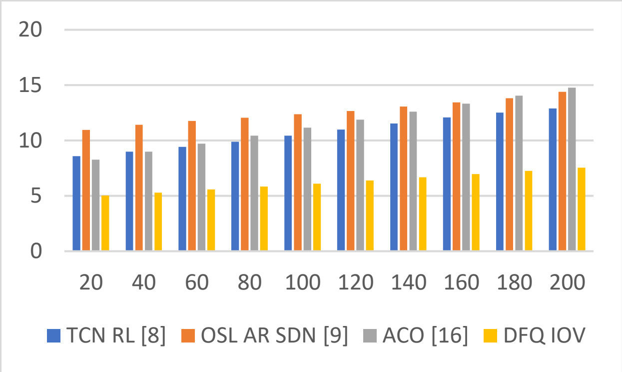

Figure 4. Average energy consumption for different IoV routing models

It can be seen from this evaluation and Fig. 4 that the proposed model has a 14.1% lower energy consumption w.r.t. TCN RL [8], nearly 18.3% lower energy consumption w.r.t. OSL AR SDN [9], and around 18.5% lower energy consumption w.r.t. ACO [16]. This makes it very useful for high network lifetime routing deployments because it consumes less energy overall. The use of leftover energy during the modelling of the routing fitness functions is the cause of this decrease in the amount of energy that was consumed. Similarly, average levels of throughput were evaluated as per equation 6, as follows,

$$T = \frac{1}{N}\sum_{i=1}^{N} \frac{P_{rx_i}}{D_i} \tag{6}$$

Where, P_{rx} & D are the number of received packets and communication delay levels. Using this strategy, average throughput for N communications can be observed from table 4 as follows,

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TABLE IV. AVERAGE THROUGHPUT FOR DIFFERENT IOV ROUTING MODELS

N	T (kbps) TCN RL [8]	T (kbps) OSL AR SDN [9]	T (kbps) ACO [16]	T (kbps) DFQ IOV
20	384.63	474.18	332.33	537.80
40	403.29	496.58	362.25	569.60
60	423.35	513.67	392.87	600.01
80	442.87	527.26	422.69	628.20
100	467.68	540.84	452.81	659.08
120	491.15	553.12	482.93	688.68
140	517.73	568.89	513.06	721.34
160	542.66	586.24	543.18	753.94
180	564.25	603.96	573.31	785.13
200	586.60	621.13	603.44	816.44

According to this assessment and Fig. 5, it can be shown that the suggested model exhibits 19.4% greater throughput w.r.t. TCN RL [8], about 18.5% better throughput w.r.t. OSL AR SDN [9], and around 19.3% better throughput w.r.t. ACO [16], which makes it very helpful for high-speed routing deployments. Fig. 5 shows a comparison of the throughputs of the proposed model with those of R1, R2, and R3. This considerable improvement in throughput may be attributed to the fact that the assessment of routes now takes into account the temporal throughput performance for each of the routes. Similarly, PDR was evaluated via equation 7, as follows,

$$PDR = \frac{1}{N}\sum_{i=1}^{N}\frac{P_{rx_i}}{P_{tx_i}} \quad (7)$$

Where, P_{tx} is the number of packets that are transmitted during each of the communications. Based on this evaluation, the PDR (P) was tabulated in table 5.

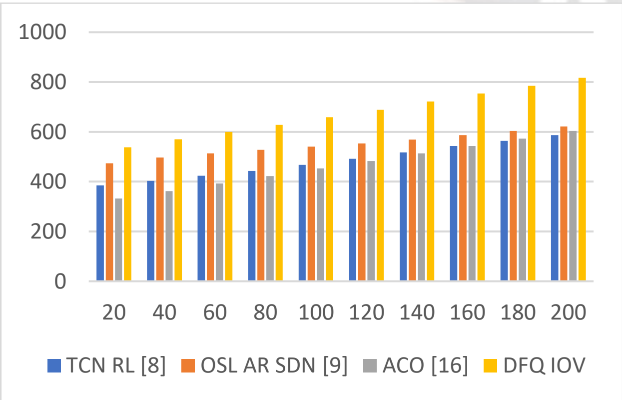

Figure 5. Average throughput for different IoV routing models

TABLE V. AVERAGE PDR FOR DIFFERENT IOV ROUTING MODELS

N	P (%) TCN RL [8]	P (%) OSL AR SDN [9]	P (%) ACO [16]	P (%) DFQ IOV
20	91.93	91.03	92.73	96.40
40	91.19	90.14	91.53	95.87
60	90.38	89.46	90.31	95.37
80	89.60	88.91	89.11	94.90
100	88.61	88.37	87.91	94.38
120	87.67	87.88	86.70	93.89
140	86.61	87.25	85.50	93.34
160	85.61	86.55	84.29	92.80
180	84.75	85.84	83.09	92.28
200	83.85	85.16	81.88	91.76

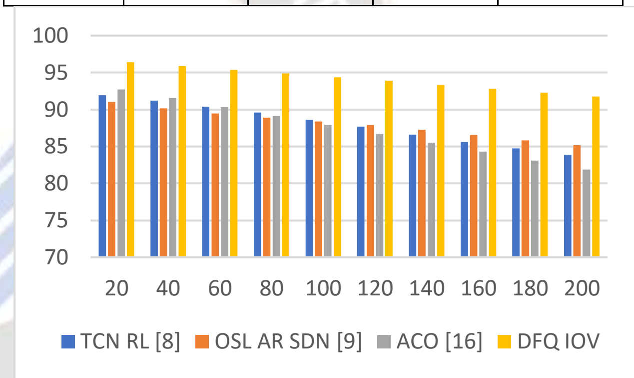

Figure 6. Average PDR for different IoV routing models

According to this analysis and Fig. 6, it is clear that the suggested model exhibits a PDR that is 8.3% better when compared to TCN RL [8], roughly 5.9% better when compared to OSL AR SDN [9], and about 10.5% better when compared to ACO [16]. This makes it very valuable for high-efficiency routing installations since it improves PDR by a wider margin than earlier models, which makes it more useful than its predecessors. The fundamental reason for this improvement in PDR is due to the incorporation of temporal PDR performance across the whole of the route estimate process. As a result of these performance gains, the solution that was presented is useful for a wide variety of IoV routing application cases.

V. CONCLUSION

The proposed routing model initially combines a highly efficient destination-aware clustering process that estimates node hop levels in order to group nodes into different fan shaped cluster sets. These groups are processed by a combined EHPSO Model that combines temporal throughput and packet delivery performance levels with instantaneous energy & distance metrics to estimate highly efficient route sets. The proposed model has a delay that is 14.5 percentage points lower in comparison to TCN RL [8], nearly 15.2 percentage points lower in comparison to OSL AR SDN [9], and approximately 10.5 percentage points lower in comparison to ACO [16]. This is achieved by combining fan clustering with EHPSO. Because of this, it is very useful for implementing high-speed routing because it reduces latency by such a significant amount. This makes it very helpful for implementing high-speed routing. The previously mentioned increase in routing speed can be traced back to the process of modelling the routing fitness functions, which included the incorporation of distance measurements as part of the process. This was the primary factor that led to the changes. In addition to this, it was discovered that the proposed model has a 14.1% lower energy consumption in comparison to TCN RL [8], nearly 18.3% lower energy consumption in comparison to OSL AR SDN [9], and approximately 18.5% lower energy consumption in comparison to ACO [16]. Because of this, it has a very low overall energy consumption, which makes it an excellent choice for high network lifetime routing deployments. This decrease in the amount of energy that was consumed is due to the utilization of unused energy during the modelling of the routing fitness functions, which was the cause of the aforementioned phenomenon. However, it was found that the proposed model has a throughput that is 19.4% higher when compared to TCN RL [8], approximately 18.5% better when compared to OSL AR SDN [9], and approximately 19.3% higher when compared to ACO [16]. This demonstrates that it is an excellent choice for high-speed routing deployments. This significant increase in throughput may be attributed to the fact that the evaluation of routes now takes into account the temporal throughput performance of each of the routes. Consequently, this improvement was made possible. When compared to TCN RL [8], OSL AR SDN [9], and ACO [16], the suggested model demonstrates a PDR that is 8.3% better than TCN RL [8], approximately 5.9% better than OSL AR SDN [9], and approximately 10.5% better than ACO [16]. Because of this, it is very useful for high-efficiency routing installations because it improves PDR by a larger margin than earlier models, which makes it more useful than its predecessors. Additionally, this makes it very valuable for high-efficiency routing installations. The incorporation of temporal PDR performance throughout the entirety of the route estimate process is the primary reason for this improvement in PDR. This improvement in PDR was achieved as a result. The solution that was presented is useful for a wide variety of IoV routing application cases as a result of the performance gains that were mentioned earlier by optimization models. In future, researchers can extend performance of the proposed model via integrating it with multiple deep learning & machine learning techniques, thereby assisting in improving its route estimation performance for different scenarios. Moreover, researchers can also integrate different bioinspired techniques including Firefly Optimization, Genetic Algorithm, Bacterial Foraging, etc. to further enhance clustering performance under multiple use cases.

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