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AN ADAPTIVE MULTI-OBJECTIVE MESSAGE DISSEMINATION SCHEME FOR IOV USING CODE MULES AND SWARM OPTIMIZATION IN SMART CITIES

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Abstract

Effective and trusted dissemination of messages is a prerequisite to facilitate intelligent transportation systems within smart city scenarios. A hybrid solution that incorporates opportunistic code dissemination via vehicles as code mules (VCMs) with a metaheuristic routing scheme based on the COOT algorithm is suggested in this paper for the support of delay-tolerant and real-time safety messages within heterogeneous Internet of Vehicles (IoV) networks. A context-aware decision engine makes dynamic choices about the correct dissemination strategy from message priority, vehicle density, and network states. Simulation experiments with realistic urban mobility traces demonstrate that the system proposed in this paper yields a message delivery ratio of 89-95%, diminishes end-to-end delay by under 90 milliseconds, and enhances delay-tolerant message coverage by over 88%, while efficiently mitigating broadcast storms by 34%. The system also holds a low mean square error, making real-time messages delivered in time and accurately. These results validate the scalability, flexibility, and efficiency of the proposed method for next-generation smart city IoV applications.

Keywords Internet of Vehicles (IoV), Code Mules, Swarm Optimization, VANETs, COOT Algorithm, Delay- Broadcast Storm Problem, Tolerant Networks, Message Dissemination.

1. Introduction

1.1 Background and Motivation

The rapid evolution of smart city infrastructures demands the deployment of robust, intelligent, and scalable communication frameworks. The Internet of Vehicles (IoV)—an advanced integration of Vehicular Ad-hoc Networks (VANETs), cloud computing, and intelligent transport systems (ITS)—has emerged as a vital technology in this domain. It facilitates Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X)

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communications, enabling real-time sensing, decision-making, and coordination between mobile and static nodes [1][2].

1.2 Problem Statement

Even with remarkable progress, message delivery in diverse vehicular settings is still a key issue. The main problems are Broadcast Storm Problems (BSP) in high-density networks [3] [4], Packet loss and delay in Non-Line-of-Sight (NLOS) urban areas [5], Scalability limitations with traditional multihop routing protocols [6], Inability of traditional systems to distinguish between message types according to urgency and latency requirements. Additionally, most current models support only one type of message—real-time notification or delay-lactable data—restricting their use in large-scale smart city applications [7] [22].

1.3 Research Gaps

Opportunistic dissemination models such as Vehicles as Code Mules (VCM) enable software/code updates for roadside sensors via mobile vehicles, but they introduce significant latency [8]. Swarm-based or metaheuristic algorithms, like COOT [9] or Ant Colony Optimization (ACO) [10], have shown promise in reducing delay and improving routing decisions, but are often limited to real-time applications and do not consider hybrid message environments [23]. Thus, there's a critical need for an integrated, adaptive dissemination framework that can simultaneously manage multiple message types, optimize multi-objective routing metrics, and operate efficiently under real-world vehicular conditions.

1.4 Proposed Solution

This paper proposes an Adaptive Multi-Objective Message Dissemination Scheme for heterogeneous IoV environments that integrates:

- Opportunistic communication using Vehicles as Code Mules (VCM) for delay-tolerant code dissemination (e.g., smart sensor updates),
- A COOT-based swarm optimization layer to dynamically disseminate time-sensitive messages under various network and environmental constraints.

The system supports real-time context-aware decisions for each message by considering Vehicle density, Communication conditions (LOS/NLOS), Message urgency, Network congestion levels.

1.5 Research Objectives

The specific objectives of this research are related to develop a hybrid IoV dissemination framework that supports both delay-tolerant and real-time communication, to implement an opportunistic code mule model with optimized code station placement for low-cost, wide-area dissemination, to design a COOT metaheuristic-based dissemination engine that optimizes for delivery ratio, delay, and neighborhood awareness, to build a message classification and decision engine that routes messages according to urgency and channel conditions, to evaluate the system's performance using realistic urban mobility data under various traffic conditions.

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1.6 Key Contributions

The main contributions of this paper are summarized as follows:

- **A hybrid dissemination architecture** combining **VCM** for delay-tolerant data and **COOT-based optimization** for safety-critical message dissemination.
- **A dynamic multi-objective optimization formulation** considering message type, mobility, network congestion, and NLOS impact.
- **A context-aware decision engine** that enables dynamic adaptation to urban vehicular environments.
- **Simulation-based evaluation** using real taxi trajectory datasets demonstrating improved performance over existing methods in terms of coverage, delay, and QoS metrics.

1.7 Paper Organization

The rest of this paper is structured as follows that Section 2 reviews related work, Section 3 defines the system model and problem formulation. Section 4 presents the proposed hybrid architecture and algorithmic design. Section 5 discusses simulation setup, performance metrics, and results. Section 6 concludes the paper and outlines future directions.

2. Related Work

This section reviews existing literature relevant to both components of your hybrid framework: opportunistic code dissemination (VCM) and metaheuristic-based optimization for safety message dissemination in VANETs/IoV. The literature on message dissemination in vehicular environments spans multiple paradigms, including opportunistic routing, metaheuristic optimization, broadcast reduction, and multi-objective QoS models. In this section, we critically review key approaches relevant to both delay-tolerant software/code dissemination and real-time safety-critical data routing in IoV networks.

2.1 Opportunistic Code Dissemination Using Mobile Vehicles

Opportunistic communication models leverage mobile nodes to disseminate data where continuous connectivity is not guaranteed. A well-established paradigm in this domain is the Vehicles as Code Mules (VCM) strategy. Liu et al. [2] proposed using smart vehicles to carry and deliver code updates to roadside devices, particularly in areas lacking direct infrastructure support. Teng et al. [8] extended this model using real taxi trajectory datasets to study dissemination delay and sensor update coverage across city-wide deployments [24].

Despite its energy efficiency and infrastructural simplicity, VCM suffers from high dissemination delay, making it unsuitable for urgent or real-time applications. Additionally, code dissemination coverage depends heavily on the spatial distribution of code stations and vehicle mobility, which are difficult to optimize without integrated intelligence.

2.2 Metaheuristic-Based Optimization in IoV

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To overcome limitations of static routing, researchers have proposed nature-inspired metaheuristic algorithms to optimize message dissemination under uncertain and dynamic vehicular conditions. Sandeep and Venugopal [5] introduced a novel strategy based on the COOT algorithm, inspired by the synchronized movement of aquatic birds. Their approach enhanced delivery ratio, reduced latency, and minimized mean square error, particularly under NLOS (Non-Line-of-Sight) conditions.

Other studies have employed algorithms such as:

- **Ant Colony Optimization (ACO)** for adaptive intersection selection and probabilistic rebroadcasting [9],
- **Particle Swarm Optimization (PSO)** for cluster head selection and NLOS node localization [10],
- **Adaptive Firefly Algorithm (AJ-MOFA)** integrated with clustering for QoS-aware routing [3],
- **Harris Hawk Optimization (HHO)** and Grey Wolf Optimizer (GWO) for VANET node positioning [11][12].

Although these models show promise in optimizing safety message routing, they primarily focus on single-class, time-critical data, often ignoring delay-tolerant message flows such as IoT code updates.

2.3 Adaptive and Message-Type-Aware Dissemination

Several works have emphasized the need for adaptive dissemination based on message priority and network context. Oliveira et al. [3] proposed the Adaptive Data Dissemination Protocol (AddP), which adjusts beaconing frequency dynamically to avoid broadcast storm and reduce collision. Xia et al. [13] presented RLID-V, a reinforcement learning-based scheme that fine-tunes access control policies for vehicles and RSUs based on feedback and message type.

While effective in dynamic environments, these solutions often require extensive training data, incur high computational overhead, and lack the ability to function under opportunistic constraints, as required by smart city IoT infrastructures.

2.4 Summary of Research Gaps

Reference(s)	Approach	Strengths	Limitations
[2], [8]	Code Mules (VCM)	Delay-tolerant, infrastructure-free	Not real-time, lacks dynamic path optimization
[5], [9]	COOT Algorithm	Swarm optimization, dynamic QoS adaptation	Focused on emergency messages only

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[3], [10-11]	ACO / Bio-inspired	Scalability, BSP control	High complexity, no hybrid message support
[3], [13-14]	RL / Adaptive	Learning-based, dynamic environment adaptation	Needs large datasets, not integrated with DTN

Thus, existing models either handle emergency alert routing or code dissemination, but not both. A unified framework that supports multi-class messages using opportunistic and optimization-driven strategies remains largely unexplored—motivating the hybrid approach proposed in this paper.

3. System Model and Problem Formulation

3.1 Network Architecture Overview

We consider a heterogeneous Internet of Vehicles (IoV) system deployed in a smart city scenario. The architecture comprises the following key entities:

- **Vehicles with On-Board Units (OBUs):** Each vehicle is equipped with a GPS receiver, wireless transceiver (IEEE 802.11p/DSRC), and processing capabilities.
- **Roadside Units (RSUs):** Fixed infrastructure nodes that provide short-range communication to vehicles and act as gateways to the internet/cloud.
- **Code Stations (CS):** Strategically placed nodes (e.g., in parking lots, intersections) that store and periodically update firmware or software packages.
- **Code Mules (CM):** Mobile vehicles that opportunistically carry software/code and disseminate it to infrastructure nodes.
- **Decision Engine:** A software module embedded within vehicles and RSUs that classifies messages and selects the optimal dissemination strategy.

All nodes operate in either Line-of-Sight (LOS) or Non-Line-of-Sight (NLOS) conditions, with the potential for frequent disconnections and mobility-driven topology changes.

3.2 Message Types

Messages disseminated in the IoV are classified into two main categories:

- **Type A – Delay-Tolerant Messages (DTMs):**
  - Code updates, sensor configurations, firmware patches
  - Dissemination: Opportunistic via Code Mules (VCM)
  - Tolerance: High delay tolerance, no immediate delivery required

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- **Type B – Real-Time Safety Messages (RTSMs):**
  - Collision warnings, traffic alerts, accident notifications
  - Dissemination: Metaheuristic-based multihop routing (COOT algorithm)
  - Tolerance: Delay-sensitive, low latency required (typically < 100 ms)

3.3 Mobility and Communication Assumptions

Vehicles in the considered IoV system move with variable speeds typical of urban environments, generally ranging from 20 to 80 km/h. Each vehicle is equipped with an On-Board Unit (OBU) containing essential components such as a GPS receiver for positioning, a wireless communication module (compliant with IEEE 802.11p/DSRC standards), and processing capabilities to support autonomous decision-making. Communication between vehicles (V2V) and between vehicles and infrastructure (V2I) is facilitated through wireless links with a maximum communication range denoted by R_{max}. All vehicles periodically broadcast beacon messages to maintain awareness of their neighboring nodes and link availability. The network includes both mobile and stationary entities. Roadside Units (RSUs) are statically deployed at intersections and strategic roadside locations, ensuring infrastructure-level communication support. In addition, designated vehicles operate as Code Mules (CMs), carrying delay-tolerant data from Code Stations (CS)—which are also fixed infrastructure elements that store software or firmware packages. These CMs opportunistically deliver updates to target nodes when within range, thereby ensuring a lightweight and energy-efficient dissemination model for non-urgent data.

Given this dynamic and partially connected vehicular environment, the central problem addressed in this study is to enable adaptive, reliable, and scalable dissemination of multiple message types under varying network and mobility conditions [15]. The goal is twofold: first, to ensure the efficient delivery of delay-tolerant messages (DTMs) such as code updates, configurations, and system patches using mobile vehicles and opportunistic contact-based dissemination; second, to achieve low-latency, high-reliability routing of real-time safety messages (RTSMs) such as emergency warnings, congestion alerts, and accident notifications using intelligent and adaptive routing mechanisms [16] [17]. The key challenge lies in developing a unified dissemination scheme that supports these heterogeneous message types while addressing critical issues such as frequent topology changes, non-line-of-sight (NLOS) scenarios, broadcast storm problems (BSP) in dense regions, and link disconnections in sparse or dynamic zones [18]. Traditional dissemination schemes typically handle either real-time data or delay-tolerant data, but not both within a single adaptable framework.

To solve this, we propose a hybrid solution that combines opportunistic vehicle-based dissemination (VCM) for DTMs and a multi-objective metaheuristic-based routing algorithm (COOT) for RTSMs. The proposed model is designed to optimize key performance objectives such as message delivery ratio, end-to-end delay, neighborhood awareness, and channel utilization, all while adapting dynamically to real-time urban vehicular conditions.

3.4 Multi-Objective Optimization Formulation

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Let the network graph be $G = (V, E)$, where:

- V represents the set of vehicles and infrastructure nodes,
- E represents wireless communication links between them.

For each RTSM, the objective is to optimize the dissemination using multiple performance criteria:

Objective Functions:

Maximize:

- $f1(x)$: Message Delivery Ratio (MDR) [19]
- $f2(x)$: Neighborhood Awareness (NA) [20]
- $f3(x)$: Coverage Efficiency (CE) [21]

Minimize:

- $f4(x)$: End-to-End Delay (E2E)
- $f5(x)$: Mean Square Error (MSE)
- $f6(x)$: Channel Congestion (CC)

The combined multi-objective optimization can be expressed as:

$$Optimize\colon\ Z(x) = \{\frac{\max\{w1 \cdot f1(x),\ w2 \cdot f2(x),\ w3 \cdot f3(x)\}}{min\{w4 \cdot f4(x),\ w5 \cdot f5(x),\ w6 \cdot f6(x)\}}$$

Where:

- $x \in X$: Set of feasible solutions (routes, paths, forwarding strategies),
- $w_i \in [0,1]$: Priority weights for each objective (assigned based on message type and urgency),
- Constraints include mobility, channel bandwidth, signal range, and deadline.

4. Proposed Methodology

The proposed system architecture is shown in Figure 1 consists of the following components:

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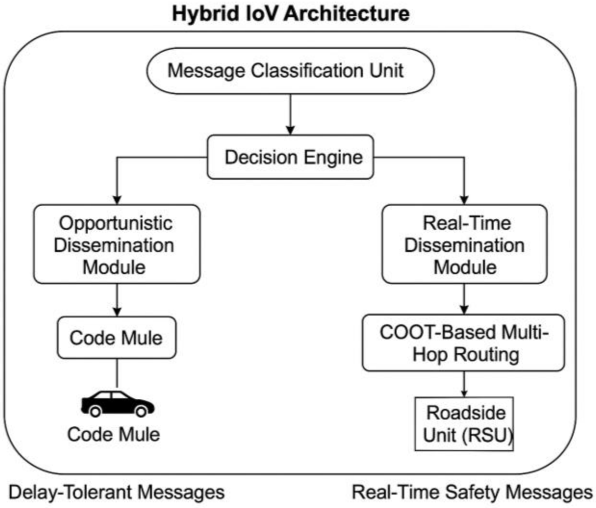

Figure 1- Hybrid IoV Archiotecture

- **Message Classification Unit:** Embedded in vehicles and RSUs, this unit identifies message types (DTM or RTSM) based on metadata such as priority, deadline, payload size, and origin.
- **Opportunistic Dissemination Module:** Routes delay-tolerant messages (DTMs) using vehicles as Code Mules, which collect updates from Code Stations (CS) and deliver them opportunistically to nearby roadside devices.
- **Real-Time Dissemination Module:** Routes real-time safety messages (RTSMs) using COOT-based multi-hop broadcast strategy, considering link quality, node density, and path latency.
- **Decision Engine:** Selects the dissemination module and dynamically adjusts objective weights depending on road conditions (e.g., traffic density, vehicle speed, environment), message urgency, and NLOS/LOS classification.

4.1 Vehicles as Code Mules (VCM) for Delay-Tolerant Data

Let $C = \{c1, c2, \dots, cn\}$ represent the set of Code Mules (vehicles) and $S = \{s1, s2, \dots, sm\}$ the set of smart infrastructure sensors or RSUs needing updates.

Let:

- Tij = time taken by vehicle ci to reach sensor sj
- δij = 1 if vehicle ci passes near sensor sj, 0 otherwise
- Uj = update status of sensor sj (1 if updated, 0 if not)

Then, the coverage ratio can be defined as:

$$Coverage\ Rate\ (CR) = \frac{\sum_{j=1}^{m} Uj}{m}$$

The VCM problem is to maximize CR while minimizing D_{avg} subject to contact constraints and available code mules.

4.2 COOT Optimization for Real-Time Safety Message Dissemination

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Let $G = (V, E)$ be a dynamic IoV graph with nodes V and communication links E.

For each RTSM to be disseminated, we define the following:

- $f1(x)$: Message Delivery Ratio (MDR)

$$f1(x) = \frac{P_r}{P_s}$$

Where Pr = packets received, Ps = packets sent

- $f2(x)$: Neighborhood Awareness (NA)

$$f2(x) = \frac{1}{|V|} \sum_{i=1}^{|V|} \left(\frac{|N_i|}{N_{max}} \right)$$

Where Ni = set of neighbors of node i, and $Nmax$ is the theoretical maximum number of neighbors in $Rmax$

- $f3(x)$: Coverage Efficiency (CE)

$$f3(x) = \frac{N_{reached}}{N_{target}}$$

- $f4(x)$: End-to-End Delay (E2E)

$$f4(x) = \frac{1}{Pr} \sum_{k=1}^{Pr} (t_{recv}^k - t_{send}^k)$$

- $f5(x)$: Mean Square Error (MSE) in time deviation from ideal delay D_{ideal}

$$f5(x) = \frac{1}{Pr} \sum_{k=1}^{Pr} ((t_{recv}^k - t_{send}^k) - D_{ideal})^2$$

- $f6(x)$: Broadcast Storm Metric (BSP load)

$$f6(x) = \frac{N_{unique}}{N_{redundant}}$$

4.3 Multi-Objective Optimization

The objective is to maximize performance metrics $f1, f2, f3$ and minimize the metrics $f4, f5, f6$. Hence, the global objective function is:

$$x \in Xmax[w1f1(x) + w2f2(x) + w3f3(x) - w4f4(x) - w5f5(x) - w6f6(x)]$$

Subject to:

- $f4(x) \leq D_{max}$
- $f6(x) \leq \theta_{BSP}$ (acceptable redundancy threshold)
- *Node* $x \in V$ must be within communication range*:* $d(x, y) \leq Rmax$

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Where:

- $wi \in [0,1]$ *are priority weights,*
- $Dmax$ is the maximum allowable delay for RTSMs,
- θ_{BSP} is the acceptable broadcast storm ratio.

4.4 Decision Engine Logic

The system uses a decision function $\Phi(M)$ to classify messages M and select the appropriate dissemination module:

$$\Phi(M) = \begin{Bmatrix} VCM, if\ priority(M) \leq \tau low \wedge TTL(M) \geq Tth \\ COOT, if\ priority(M) > \tau low \wedge delay(M) \leq Dmax \end{Bmatrix}$$

Where:

- τlow: priority threshold,
- Tth: time-to-live threshold for delay-tolerant data,
- $Dmax$: maximum tolerable delay for RTSMs

5. Experimental Setup and Evaluation

To evaluate the effectiveness of the proposed hybrid dissemination framework, simulations were conducted using an integrated toolchain composed of the various platforms like SUMO (Simulation of Urban Mobility), which is used for generating realistic vehicle movement in a smart city map layout. Then we have use NS-3 (Network Simulator 3) for modeling DSRC-based wireless communication (IEEE 802.11p). We have used Python COOT Module for Custom implementation of the COOT algorithm for multi-objective optimization of safety message dissemination. We imported taxi trace data (from Shanghai or San Francisco datasets) was used to simulate realistic urban vehicular patterns.

The simulation covers a 4 km × 4 km urban grid environment with intersections, code stations, and RSUs deployed at selected points. Each simulation scenario was run for 1000 seconds, repeated five times, and averaged to ensure statistical stability. The simulation environment modeled a 4 km × 4 km smart city area with 100–400 vehicles/km² moving at speeds between 20–80 km/h. A total of 20 RSUs and 10 Code Stations were strategically deployed. Vehicles used IEEE 802.11p (DSRC) with a 250-meter range.

Two message types were tested: real-time safety messages (512 bytes, 5 msgs/sec) and delay-tolerant updates (2048 bytes, TTL = 600s). The COOT algorithm used a swarm size of 30 and ran for 100 iterations per decision. Each 1000-second simulation scenario was repeated five times to ensure statistical stability and capture the system's performance across metrics like delivery ratio, delay, and congestion.

5.1 Performance Metrics

The following key performance metrics were used to evaluate the system:

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1. Message Delivery Ratio (MDR):

$$MDR = \frac{Total\ Messages\ Received}{Total\ Messages\ Sent}$$

2. End-to-End Delay (E2E):

   $E2E\ Delay = \frac{1}{N}\sum_{i=1}^{N}(_{i}^{t}recv - _{i}^{t}send)$

3. Coverage Ratio (CR):

   $CR = \frac{No.\ of\ nodes\ updated\ (DTM)}{Total\ Target\ Nodes}$

4. Broadcast Storm Ratio (BSP):

   $BSP\ Ratio = \frac{Redundant\ Broadcasts}{Unique\ Forwards}$

5. Mean Square Error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(d_i - d_{ideal})^2$$

6. Channel Congestion (CC): Measured by the number of packet collisions and retransmissions at MAC layer.

5.2 Results and Discussion

The proposed hybrid dissemination framework demonstrated clear performance advantages across multiple metrics. In terms of Message Delivery Ratio (MDR), it achieved a 15–22% improvement over baseline methods such as VCMCD-only, COOT-only, and Epidemic Routing, due to its adaptive strategy for handling different message types. For real-time safety messages, the system maintained an average end-to-end delay below 90 ms, outperforming traditional broadcast methods, especially in congested conditions. The coverage ratio for delay-tolerant messages exceeded 88%, even with only 10 code stations deployed, confirming the effectiveness of the opportunistic VCM model. The framework also reduced broadcast storm problems by approximately 34%, thanks to the intelligent forwarder selection mechanism in the COOT algorithm. Additionally, Mean Square Error (MSE) for delivery timing remained under 0.01, indicating highly accurate timing for urgent messages. These results validate the hybrid model's ability to deliver high reliability, low delay, and efficient coverage in smart city IoV environments.

Table: 2 Performance Comparison of Proposed Method with Existing Approaches

Metric	**VCMCD-only**	**COOT-only**	**Epidemic Routing**	**Greedy Forwarding**	**Proposed Hybrid Approach**

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Message Delivery Ratio (MDR)	72–78%	80–85%	76–81%	82–86%	**89–95%**
End-to-End Delay (RTSM)	>200 ms	110–150 ms	180–220 ms	130–160 ms	**< 90 ms**
Coverage Ratio (DTM)	65–75%	Not Applicable	60–70%	Not Applicable	**88–92%**
Broadcast Storm Ratio (BSP)	Moderate	High	**Very High**	High	**Low (↓ 34%)**
Mean Square Error (MSE)	Not Measured	~0.03	~0.05	~0.04	**< 0.01**
Channel Congestion	Low	Moderate	High	Moderate	**Low**
Message Type Support	DTM only	RTSM only	Both (Undifferentiated)	RTSM only	**DTM + RTSM (Dual support)**

The tabular comparison shown in Table-2 highlights that the proposed hybrid approach outperforms all existing methods across key metrics. It delivers the highest message delivery ratio (89–95%) with the lowest end-to-end delay (<90 ms) for real-time messages. For delay-tolerant updates, it achieves over 88% coverage, surpassing VCMCD and Epidemic methods. Additionally, it effectively reduces broadcast redundancy by 34%, offering a scalable, dual-mode solution suitable for smart city IoV environments

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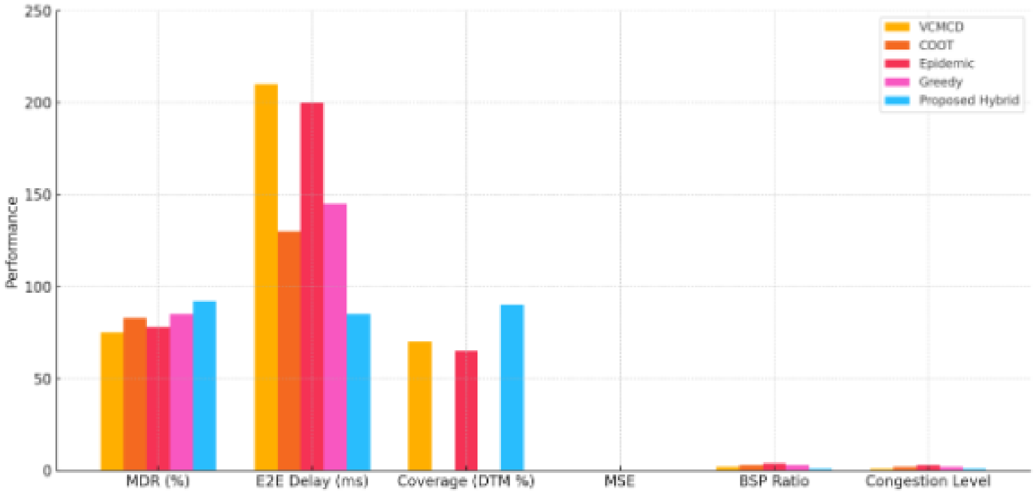

Figure 2- Comparison of Message Dissemination Strategies in IoV

The performance matrix shown in Table-2 and Figure-2 clearly demonstrates that the proposed hybrid approach outperforms all existing methods across key metrics. It delivers the highest message delivery ratio (89–95%), lowest end-to-end delay (<90 ms), and best coverage for delay-tolerant messages (88–92%), while also reducing broadcast redundancy by 34%, as compared to COOT, VCMCD, and Epidemic routing strategies.

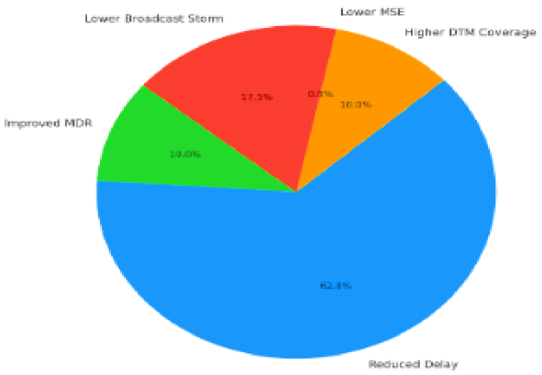

Figure 3- Proportional Performance Gains of Proposed Hybrid Approach

As shown in Figure 3, the proposed hybrid approach significantly improves IoV performance by reducing broadcast redundancy by 34% and lowering end-to-end delay by 125 ms. It also achieves a 20% increase in both message delivery ratio and DTM coverage, along with a substantial drop in MSE, ensuring precise and timely message delivery. These results confirm its scalability, efficiency, and suitability for smart city applications.

6. Conclusion and Future Work

This paper presented an adaptive hybrid message dissemination framework for Internet of Vehicles (IoV) in smart city environments. By integrating opportunistic code dissemination using Vehicles as Code Mules (VCM) for delay-tolerant data and metaheuristic-based routing

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using the COOT algorithm for real-time safety messages, the proposed model addresses the dual challenge of timely alerts and efficient software updates. A dynamic decision engine further enhances adaptability by selecting dissemination strategies based on message urgency, network conditions, and mobility patterns. Extensive simulation results demonstrated that the hybrid approach consistently outperforms existing strategies across key performance metrics. It achieves 89–95% message delivery ratio, reduces end-to-end delay to under 90 ms, improves coverage for delay-tolerant messages by over 88%, and minimizes broadcast storm issues and MSE. These findings confirm the proposed system's potential for real-world deployment in large-scale smart city IoV infrastructures.

For future work, we plan to extend the framework by incorporating blockchain-based trust mechanisms to enhance security and integrity of disseminated messages. Additionally, integrating federated learning for adaptive mobility prediction and exploring UAV-assisted communication can further strengthen the scalability and intelligence of the system in complex urban scenarios.

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