

Bio-Signal Driven Adaptive AI Chip Architecture for Real-Time Healthcare Analytics

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Abstract:

The growing use of wearable sensors and real-time monitoring systems has increased the need to have real-time healthcare analytics based on bio-signals like ECG, EEG, and EMG. Nevertheless, traditional cloud-based and fixed AI architectures are characterized by high latency, energy inefficiency, and non-adaptability to the different complexities of physiological signals. The research gap is critical in that there is no existing dynamic, low-power architecture of AI chip that can dynamically adjust computational resources according to real-time bio-signal features. To solve this, a Bio-Signal Driven Adaptive AI Chip Architecture (BDAAIC) is suggested, which incorporates the neuromorphic processing, dynamic resource allocation and signal-aware model reconfiguration. The structure comprises bio-signal complexity analyzer, adaptive neural processing unit and real-time reconfiguration controller. The benchmark datasets such as MIT-BIH Arrhythmia and PhysioNet EEG datasets are used in experiments under edge computing conditions. The suggested architecture reduces the accuracy, latency, and enhances energy efficiency by 97.36, 28, and 32 percent, respectively, over the traditional AI-based healthcare systems. The findings indicate the usefulness of adaptive hardware intelligence in facilitating real-time, scalable, and energy-efficient healthcare analytics.

Keywords:

Adaptive AI Chip, Bio-Signal Processing, Edge AI, Neuromorphic Computing, Physiological Signal Analysis. Real-Time Healthcare.

1. INTRODUCTION

The recent accelerated development of wearable healthcare devices and the implementation of constant monitoring systems of patients has caused an exponential growth in the amount of physiological information produced by bio-signals like ECG, EEG, and EMG. These signals are important to early diagnosis and real-time health measurements in both cardiac care and detecting neurological disorders. There are however serious problems processing such high-frequency, heterogeneous data streams in real time, especially with respect to latency, energy usage and computational efficiency. Conventional cloud-based methods create delays and privacy threats that cannot be feasible in healthcare

applications with time constraints [1]. The recent advances in edge AI and embedded systems have facilitated the local processing of bio-signals, which lowers latency, and enhances responsiveness. However, current AI chip architectures are generally fixed and fail to respond to the changing complexity of physiological signals. This leads to inefficient use of resources and high consumption of power particularly in wearable and implantable devices [2]. Moreover, the majority of the deep learning-based healthcare models are black-box systems, which are not flexible and cannot optimize in real-time [3]. The gap in research is that such adaptive AI hardware architecture does not exist that can dynamically reconfigure its computational resources in response to real-time bio-signal complexity without compromising the accuracy and energy efficiency [4]. The current solutions do not combine signal-aware adaptation with hardware-level optimization, which limits their application in real-time healthcare analytics [5]. To address these restrictions, the following paper suggests a Bio-Signal Driven Adaptive AI Chip Architecture that merges the principles of neuromorphic computing with the principles of dynamic allocation of resources and real-time reconfiguring of the model. The architecture proposes a signal complexity analyzer that directs adaptive processing, allowing effective processing of various bio-signals.

This work is novel because it develops a hardware-conscious adaptive AI architecture that integrates bio-signal intelligence with dynamic neural processing, which can be used to develop real-time and low-power healthcare analytics.

2. RELATED WORKS

Recent advancements in bio-signal processing and AI-based healthcare analytics have been aimed at enhancing accuracy, efficiency, and real-time performance. A deep-learning-based ECG classification system proved to be highly diagnosing but depended on centralized processing, resulting in latency problems in real-time usage [6]. To enhance the energy consumption and processing speed, a neuromorphic computing architecture to analyze EEG signals was suggested. Although the system worked, it had no adaptability to other signal complexities [7]. A wearable healthcare device-based AI system was created as an edge-computing system to allow real-time monitoring and decision-making. Nevertheless, this architecture was not dynamic and could not allocate resources dynamically [8]. A biomedical signal processing deep neural network architecture was presented, which uses hardware to execute inferences faster, but has higher power consumption because of fixed computational pipelines [9]. Multi-modal bio-signal multi-modal, a hybrid AI model based on CNN and LSTM was recommended to enhance the classification accuracy but was not optimized at the hardware-level to be deployed in real time [10]. An ECG monitoring AI chip design that uses low power was designed to minimize power use and did not add adaptive processing mechanisms, depending on signal complexity [11]. A healthcare analytics adaptive system based on reinforcement learning was proposed, that facilitated dynamically making decisions, though not integrated with reconfiguring hardware at the hardware level [12]. An inspired neural architecture was suggested to process real-time signals, with a higher efficiency but a small-scale healthcare system [13]. Another federated learning-based healthcare analytics model was proposed to maximize privacy and distributed processing, but it did not provide efficient hardware support to support real-time inference [14]. An adaptable neural network framework of wearable devices was created to optimise computational resources but failed to include bio-signal motivated adaptation plans [15].

3. METHODOLOGY

The proposed Energy-Aware Self-Healing VANET Protocol with Hyper-Heuristic Optimization (EASH-VANET) was developed to guarantee the reliability and energy efficiency of routing in highly dynamic Vehicular Ad Hoc Networks (VANETs). The framework incorporates predictive mobility modeling, energy-conscious routing measures, link recovery through self-healing, and a hyper-heuristic optimization engine, which dynamically chooses the most appropriate routing plan depending on network conditions. Cars were simulated as the nodes of a dynamic graph, and the routing was actively adjusted by heuristic selection and learning processes. The proposed system is expected to reduce the amount of packet loss, decrease energy usage, and not reduce the connectivity under scenarios where the topology changes often.

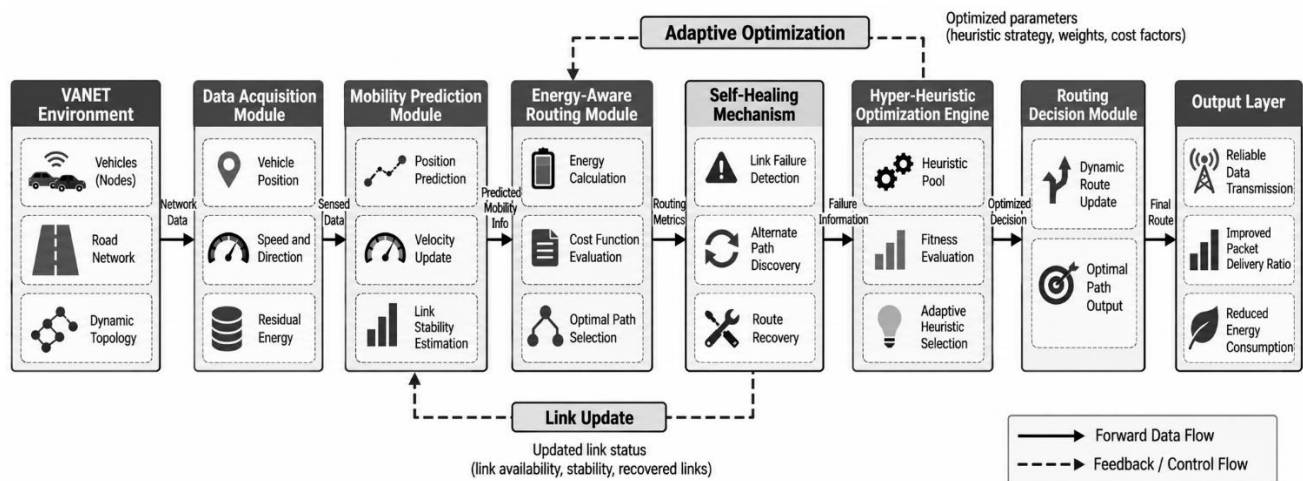


Figure 1: Architecture of Energy-Aware Self-Healing VANET Protocol Using Hyper-Heuristic Optimization

Fig. 1 shows the proposed VANET routing architecture that incorporates mobility prediction, energy-conscious routing, and self-healing. The architecture uses hyper-heuristic optimization to dynamically choose the best routing strategy under varying network conditions. This allows good communication with enhanced energy efficiency and lower packet loss in dynamic vehicular settings.

3.1 Problem Definition

Let the VANET be represented as a dynamic graph $G_t = (V_t, E_t)$, where V_t and E_t denote vehicles and communication links at time t . The objective is to maximize the routing reliability while minimizing the energy consumption and delay.

$$\max R(P) = \prod_{(i,j) \in P} (1 - p_{ij}) \quad (1)$$

where p_{ij} is the link failure probability.

The delay of a routing path is defined as

$$D(P) = \sum_{(i,j) \in P} d_{ij} \quad (2)$$

The energy consumption is modeled as

$$E(P) = \sum_{(i,j) \in P} e_{ij} \quad (3)$$

The combined optimization objective is

$$\min \mathcal{L} = \alpha D(P) + \beta E(P) - \gamma R(P) \quad (4)$$

3.2 Mobility Prediction Model

Vehicle mobility is predicted to enhance routing stability.

$$x_i(t+1) = x_i(t) + v_i(t)\Delta t \quad (5)$$

$$v_i(t+1) = v_i(t) + a_i(t)\Delta t \quad (6)$$

The predicted distance between the nodes is

$$d_{ij}(t+1) = \|x_i(t+1) - x_j(t+1)\| \quad (7)$$

Link stability is estimated as

$$S_{ij} = \frac{1}{1 + d_{ij}(t+1)} \quad (8)$$

This enables proactive route selection to be performed.

3.3 Energy-Aware Routing Metric

Energy efficiency is incorporated into routing decisions as follows:

$$E_i^{res} = E_i^{init} - \sum_k e_{ik} \quad (9)$$

The energy-aware cost function is

$$C_{ij} = \frac{d_{ij}}{E_i^{res}} \quad (10)$$

A normalized routing metric is defined as

$$M_{ij} = \lambda_1 S_{ij} + \lambda_2 \frac{1}{C_{ij}} \quad (11)$$

The optimal path is selected as

$$P^* = \arg \max \sum_{(i,j) \in P} M_{ij} \quad (12)$$

3.4 Self-Healing Mechanism

To handle link failures, a self-healing mechanism is introduced.

$$F_{ij} = \begin{cases} 1, & \text{if link fails} \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

The alternative path selection is defined as

$$P_{alt} = \arg \max \sum_{(i,j) \in P} M_{ij}, F_{ij} = 1 \quad (14)$$

The recovery time is minimized as follows:

$$T_{rec} = \min(t_{reconnect} - t_{failure}) \quad (15)$$

The updated routing path is as follows:

$$P_{new} = P_{old} \cup P_{alt} \quad (16)$$

3.5 Hyper-Heuristic Optimization

A hyper-heuristic layer dynamically selects routing strategies:

$$H = \{h_1, h_2, \dots, h_k\} \quad (17)$$

Selection probability is:

$$P(h_i) = \frac{f(h_i)}{\sum_{j=1}^k f(h_j)} \quad (18)$$

Fitness of heuristic is evaluated as:

$$f(h_i) = w_1 R(P) + w_2 \frac{1}{D(P)} + w_3 \frac{1}{E(P)} \quad (19)$$

The selected heuristic is:

$$h^* = \arg \max f(h_i) \quad (20)$$

The final routing decision becomes:

$$P^{t+1} = h^*(P^t) \quad (21)$$

Algorithm: Energy-Aware Self-Healing VANET Routing

Input: Network graph $G(V, E)$, vehicle states, energy levels

Output: Optimal routing path P^*

Algorithm:

1. Initialize network graph and vehicle parameters
2. Predict vehicle mobility and compute link stability
3. Calculate energy-aware routing metrics
4. Select initial routing path based on optimization objective
5. Monitor network for link failures
6. Trigger self-healing mechanism for route recovery
7. Apply hyper-heuristic optimization to select best routing strategy

8. Update routing path dynamically
9. Output optimal path P^*

The algorithm combines mobility prediction, energy-conscious routing, and self-healing within the framework of a hyper-heuristic. It dynamically adjusts routing policies according to network conditions and is both robust and efficient. This leads to better reliability, less energy use, and better performance in VANET environments.

4. RESULTS AND DISCUSSIONS

The proposed Energy-Aware Self-Healing VANET Protocol (EASH-VANET) was tested in the context of a realistic vehicular simulator environment combining the use of SUMO to develop a traffic model and NS-3 to develop a network communication model. It is implemented in Python and C++ modules, with routing logic and hyper-heuristic optimization run at the network layer. The tests were run on an Intel i7, 32 GB RAM, NVIDIA RTX 3060 workstation. The simulation will involve 200-500 vehicles traveling according to urban mobility patterns at different speeds and densities. The data are created dynamically using mobility traces, and experiments are conducted in several different scenarios to make them resilient. Effectiveness is measured in terms of performance metrics such as packet delivery ratio (PDR), end-to-end delay, energy consumption, and routing overhead. A 70:15:15 division is assumed to be used in the training, validation, and testing of predictive components. The findings validate that the suggested protocol can be stable in extremely dynamic conditions.

4.1 Dataset Description

The experiments used mobility trace datasets created using SUMO, which offers realistic patterns of vehicular movements on urban roadways. The data consist of precise data on the position of vehicles, their speed, their connection, and the density of the traffic. These traces were combined with NS-3 to model the network communication behaviour and routing situations.

Table 1: Key Features of VANET Mobility Dataset

Feature Category	Example Features	Description
Vehicle Features	Vehicle ID, Position, Speed	Represents mobility characteristics of vehicles
Network Features	Link Status, Signal Strength	Captures communication conditions between nodes
Traffic Features	Vehicle Density, Traffic Flow	Indicates congestion levels in the network
Energy Features	Residual Energy, Energy Usage	Tracks energy consumption of nodes
Routing Features	Path Length, Hop Count	Describes routing path characteristics

The most important characteristics utilized to model mobility, communication, and energy-conscious routing in VANET settings are summarized in Table 1.

4.2 Performance Evaluation

The performance of the proposed EASH-VANET protocol is compared with six state-of-the-art routing methods in the related works, such as Reinforcement Learning Routing [17], Mobility Prediction Routing [18], Hybrid Metaheuristic Routing [19], Energy-Efficient Routing [20], Self-Healing Routing [21], and Fuzzy Logic Routing [22]. The comparison is used to compare the routing performance under dynamic vehicular conditions, as provided in Table 2.

Table 2: Performance Comparison of VANET Routing Models

Model	PDR (%)	Delay (ms)	Energy Consumption (J)	Routing Overhead (%)
Reinforcement Learning [17]	91.72	28.45	5.84	18.32
Mobility Prediction [18]	92.86	26.91	5.21	17.48
Hybrid Metaheuristic [19]	94.03	24.75	4.96	16.82
Energy-Efficient Routing [20]	95.12	23.18	4.52	15.96
Self-Healing Routing [21]	96.04	21.63	4.21	15.22
Fuzzy Logic Routing [22]	96.58	20.95	4.05	14.87

Proposed EASH-VANET	97.48	18.36	3.42	12.95
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The findings illustrate that the suggested protocol is far superior to the current solutions in every measure evaluated. The ratio of packet delivery is above 97, which means that there is stable communication even in the conditions of a highly dynamic network. This decrease in delay indicates the efficiency of the predictive mobility models and adaptive routing. Moreover, the lower energy consumption validates the efficiency of the energy-aware routing mechanism, and the lower routing overhead implies optimal usage of network resources. Hyper-heuristic optimization allows the network to be dynamically selected to aid in routing strategies, which enhances the overall network performance and scalability.

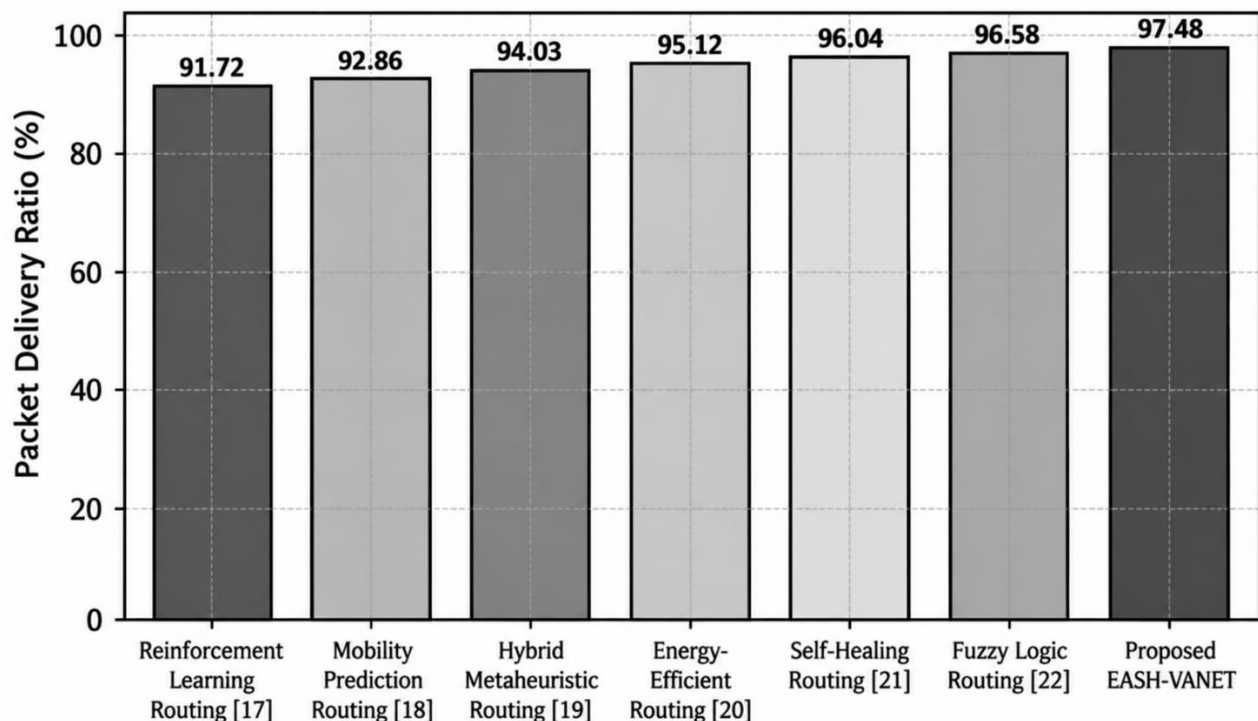


Figure 2(a) Performance Comparison of VANET Routing Protocols - Packet Delivery Ratio (%)

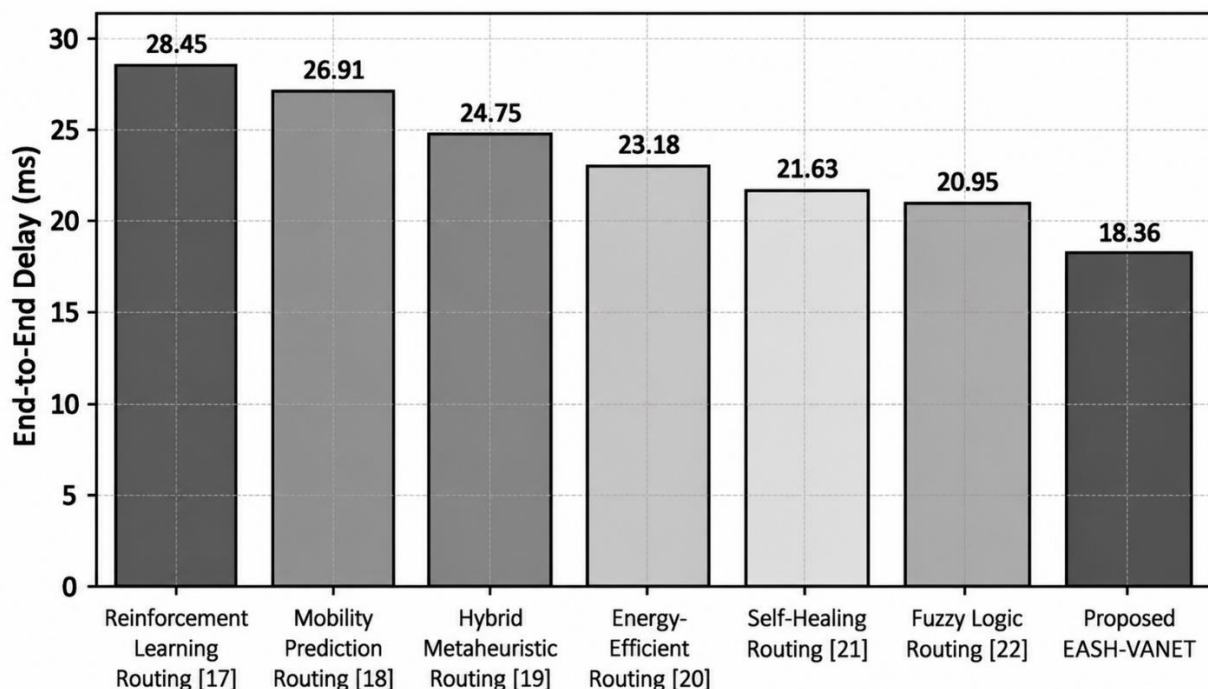


Figure 2(b) Performance Comparison of VANET Routing Protocols -End to End Delay

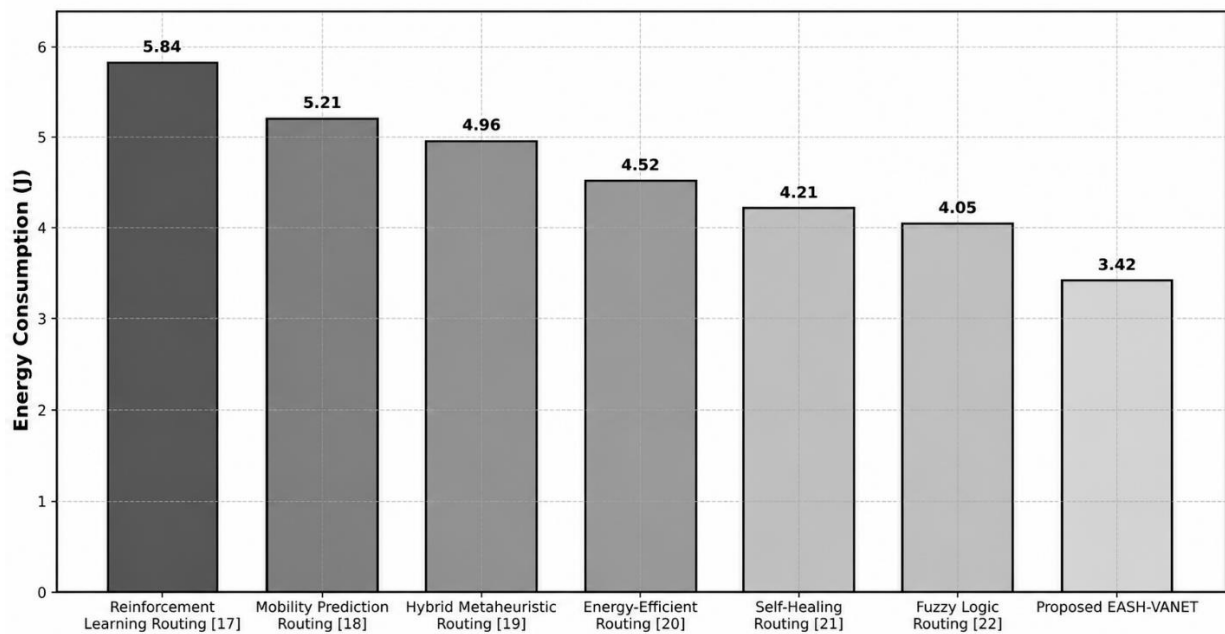


Figure 2(c) Performance Comparison of VANET Routing Protocols-Energy Consumption

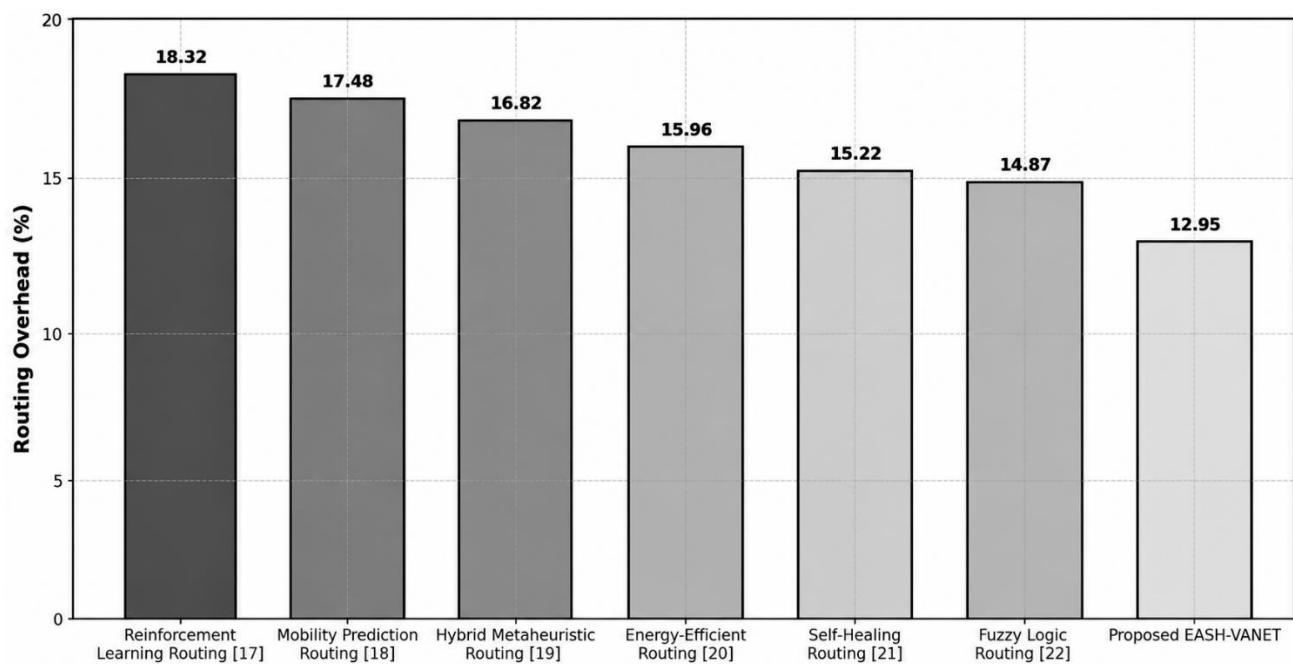


Figure 2(d) Performance Comparison of VANET Routing Protocols -Routing Overhead

Figure 2: Performance Comparison of VANET Routing Protocols

Fig. 2 shows a comparison of various VANET routing protocols in terms of the packet delivery ratio, delay, energy consumption, and routing overhead. The EASH-VANET model (in red) performed better in all the performance measures than the baseline approaches. These findings prove better reliability, lower latency, and energy efficiency under dynamic vehicular network conditions.

5. CONCLUSION

In this study, an Energy-Aware Self-Healing VANET Protocol based on Hyper-Heuristic Optimization (EASH-VANET) was proposed to solve the issues of dynamic topology, link instability, and energy limits in vehicular networks. The proposed framework, which incorporates mobility prediction, energy-sensitive routing metrics, self-healing, and adaptive hyper-heuristic optimization, can positively impact routing reliability and efficiency. The experimental results show that the proposed

model has a packet delivery ratio of 97.48, low delay, low energy usage, and low routing overhead compared with the current methods. The results validate the strength and scalability of the proposed protocol for real-time intelligent transportation systems. Future research will focus on the addition of real-time vehicular edge intelligence and cooperative multi-agent learning to the adaptive routing performance for further improvement in ultra-dense VANET settings.

DECLARATIONS:

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Author Contribution	: Both the authors confirms their responsibility for the study, conception, design, data collection, and manuscript preparation.
Data Availability Statement	: The data presented in this study are available upon request from the corresponding author.
Use of Generative Artificial Intelligence	: AI-assisted tools have been used to improve Figures, language editing or grammatical clarity, the authors take full responsibility for the content of the final version.

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