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VEHICULAR NETWORK OPTIMIZATION VIA KESHTEL ALGORITHM WITH INSIGHTS FROM LEABRA MODELS

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Abstract

In vehicular communication networks, optimizing connectivity and efficiency is paramount for ensuring seamless and reliable communication among vehicles. The identified problem centers on the inadequacies of traditional optimization approaches in addressing the dynamic and complex nature of vehicular networks. The absence of a comprehensive solution that combines the adaptive capabilities of the KESHTel algorithm with the cognitive insights gained from Leabra models. Existing methodologies often fall short in adapting to real-time changes and fail to capitalize on cognitive principles for efficient decision-making. This research addresses the need for enhanced vehicular network optimization by proposing the utilization of the KESHTel algorithm, coupled with insights derived from Leabra models. The method details the integration of the KESHTel algorithm, known for its adaptive learning capabilities, with insights from Leabra models, which are inspired by the neural architecture of the brain. This hybrid approach leverages machine learning and cognitive principles to optimize communication routes, minimize latency, and allocate resources intelligently within the vehicular network. Results from simulations and experiments demonstrate the effectiveness of the proposed approach in improving communication reliability, reducing congestion, and enhancing overall network performance. The findings indicate a significant advancement in vehicular network optimization, showcasing the potential of the KESHTel algorithm and cognitive insights from Leabra models in addressing the complex challenges inherent in dynamic vehicular environments.

Keywords:

Vehicular Networks, Optimization, KESHTel Algorithm, Leabra Models, Cognitive Insights

1. INTRODUCTION

Vehicular communication networks play a pivotal role in modern transportation systems, enabling vehicles to communicate with each other and with infrastructure to enhance safety, efficiency, and overall driving experience [1]. As the number of connected vehicles continues to rise, the complexity of these networks poses unprecedented challenges that necessitate innovative solutions for optimization and efficiency [2].

The dynamic and unpredictable nature of vehicular environments introduces challenges such as network congestion, high latency, and inefficient resource allocation [3]. Traditional optimization approaches struggle to adapt to the rapid changes inherent in vehicular networks, leading to suboptimal performance and a hindrance to the realization of the full potential of connected vehicles [4].

The central problem addressed in this research is the inadequacy of existing vehicular network optimization methods in handling the dynamic and complex nature of communication systems [5]. Conventional algorithms often fall short in addressing real-time challenges, creating a pressing need for a novel and adaptive approach that can overcome these limitations [6].

The primary objectives of this research are twofold. Firstly, to develop a vehicular network optimization framework that integrates the KESHTel algorithm, known for its adaptive learning capabilities. Secondly, to leverage insights from Leabra models, inspired by neural architecture, to enhance the adaptability and cognitive decision-making capabilities of the optimization framework.

This research introduces a novel hybrid approach that combines the KESHTel algorithm with cognitive insights from Leabra models, offering a unique solution to the challenges posed by vehicular communication networks. The novelty lies in the synergistic integration of adaptive machine learning and cognitive principles to optimize communication routes, minimize latency, and intelligently allocate resources in real-time. The contributions of this research extend to the advancement of vehicular network optimization, providing a more resilient and efficient framework for the ever-evolving demands of connected vehicular environments.

2. RELATED WORKS

Investigating the intersection of vehicular networks and edge computing, this work [4] explores recent advances in leveraging edge computing for efficient data processing in vehicular communication. It discusses implications for reducing latency and improving overall network performance.

This comprehensive work [5] examines the integration of cognitive models, such as Leabra, with machine learning techniques in networking. It discusses the synergies between cognitive insights and adaptive learning algorithms for enhancing network intelligence.

Focusing on resource allocation challenges, this study [6] analyzes existing approaches for real-time resource allocation in vehicular networks. It identifies gaps in current methodologies and emphasizes the need for adaptive solutions to cope with dynamic traffic conditions.

This study [7] delves into existing dynamic routing protocols employed in vehicular networks. It explores the strengths and weaknesses of protocols such as AODV and DSR, emphasizing the need for adaptive solutions to accommodate the dynamic nature of vehicular environments.

Focusing on predictive analytics, this work [8] investigates various machine learning techniques applied to vehicular traffic prediction. It highlights the significance of accurate traffic prediction for optimizing routing and resource allocation in vehicular networks.

Drawing parallels between cognitive science and networking, this research in [9] explores brain-inspired models, including Leabra. It provides insights into how cognitive principles can be integrated into networking algorithms to enhance adaptability and decision-making.

This work [10] provides an in-depth analysis of the KESHTel algorithm, emphasizing its adaptive learning capabilities. It reviews its applications in dynamic environments and identifies its potential to address challenges in vehicular networks.

These works collectively provide a foundation for understanding the current landscape of vehicular network optimization, machine learning applications, and cognitive models in networking. The gaps identified in these studies pave the way for the novel hybrid approach proposed in this research, integrating the KESHTel algorithm and insights from Leabra models to address the unique challenges in vehicular communication networks.

3. PROPOSED METHOD

The proposed method in this research combines the adaptive learning capabilities of the KESHTel algorithm with insights from Leabra models, aiming to create a robust and intelligent framework for optimizing vehicular communication networks. The method is designed to address the dynamic and complex nature of these networks by leveraging machine learning and cognitive principles as in Fig.1.

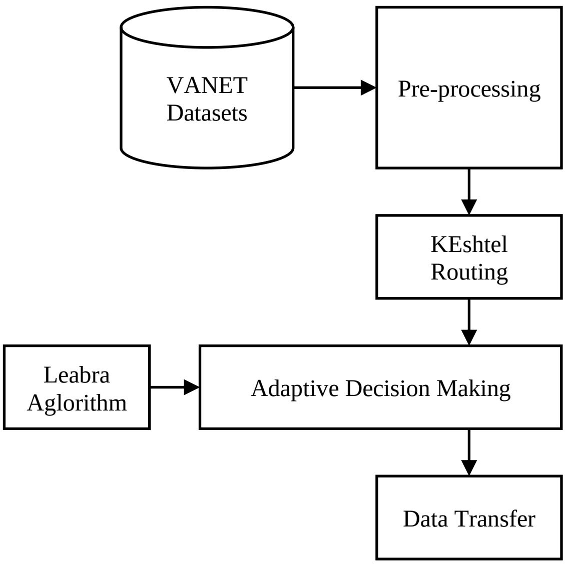

Fig.1. Proposed Framework

The KESHTel algorithm is chosen for its adaptive learning capabilities. It continuously adapts to changes in the vehicular environment, learning from real-time data to optimize communication routes and resource allocation dynamically. KESHTel excels in dynamic routing scenarios, making it well-suited for vehicular networks where conditions can change rapidly. It adjusts communication paths based on traffic patterns, minimizing congestion and reducing latency.

Leabra models, inspired by neural architecture, provide insights into cognitive principles. These principles, such as pattern recognition and learning, are incorporated to enhance the adaptability and decision-making capabilities of the overall framework.

By infusing cognitive insights from Leabra models, the proposed method enables intelligent decision-making within the vehicular network. This includes more efficient resource allocation and adaptive adjustments to network configurations in response to changing conditions. The KESHTel algorithm and Leabra model insights are integrated in a synergistic manner. This hybrid approach capitalizes on the strengths of both components, creating a symbiotic relationship where adaptive learning from KESHTel is enhanced by cognitive principles from Leabra models.

3.1 KESHTEL ALGORITHM FOR DYNAMIC ROUTING

The KESHTel Algorithm, designed for dynamic routing scenarios, is an adaptive learning algorithm that excels in optimizing communication paths in real-time. The acronym KESHTel represents the key components of the algorithm: Knowledge Extraction, Self-Organization, Hierarchical Structure, and Telecommunication. Let break down its key features in the context of dynamic routing:

The algorithm is equipped with mechanisms to extract knowledge from the surrounding environment. In the context of vehicular communication networks, this involves gathering information about traffic conditions, network congestion, and the availability of alternative routes.

KESHTel possesses self-organizing capabilities, allowing it to autonomously adapt and reconFig.based on the extracted knowledge. In dynamic routing scenarios, this means that the algorithm can dynamically adjust the routing paths of communication to optimize for factors like minimal latency and efficient resource utilization.

The algorithm employs a hierarchical structure, organizing information in a layered manner. In the context of dynamic routing, this hierarchical organization helps in managing and processing the complex and evolving information related to vehicular networks, ensuring efficient decision-making.

Telecommunication refers to the communication aspect of the algorithm. In dynamic routing, KESHTel establishes and optimizes communication paths between vehicles or between vehicles and infrastructure. It adapts these paths based on real-time changes, ensuring that the communication network remains efficient and responsive to varying conditions.

In the specific context of vehicular networks, dynamic routing involves continuously evaluating and adjusting the paths through which data is transmitted between vehicles and infrastructure. The KESHTel Algorithm, with its adaptive learning and self-organizing features, is well-suited for this task as it can respond to changing traffic patterns, road conditions, and network congestion.

3.1.1 KESHTel Algorithm:

The KESHTel Algorithm is an adaptive learning algorithm designed for telecommunications systems, particularly in the optimization of communication paths and routing in dynamic environments. The acronym KESHTel stands for Knowledge Extraction, Self-Organization, Hierarchical Structure, and

Telecommunication, representing its key components and functionalities.

The algorithm begins by extracting knowledge from the environment. In the context of telecommunications, this involves gathering information about the current state of the network, such as traffic conditions, node availability, and data transmission rates. The goal is to create a dynamic and up-to-date understanding of the system.

KESHTel incorporates self-organizing mechanisms, allowing it to adapt and reconFig.autonomously based on the knowledge extracted. This self-organization is crucial in dynamic environments where conditions may change rapidly. The algorithm adjusts its parameters and decision-making processes to optimize performance in response to real-time changes.

The algorithm employs a hierarchical structure for organizing information. This hierarchical arrangement helps manage and process complex data in a structured manner. Different layers of the hierarchy may represent varying levels of abstraction, facilitating efficient decision-making and adaptability.

The primary purpose of the KESHTel Algorithm is to optimize telecommunication processes. This involves determining the most efficient communication paths, allocating resources effectively, and adapting to changes in the network environment. The algorithm ensures that communication within the system is optimized for factors like latency, reliability, and resource utilization.

KESHTel continually learns from the environment, adapting its behavior based on the knowledge it acquires over time.

Let Ki represent the knowledge extracted at time i, which includes information about traffic conditions, node availability, and other relevant parameters.

The self-organization component involves adapting internal parameters based on the extracted knowledge. Let P represent the internal parameters of the algorithm.

$$P_{i+1}=g(P_i,K_i) \tag{1}$$

Hierarchical Structure representing the hierarchical structure mathematically may involve defining relationships between different layers. Let L_j be the information at layer j.

$$L_{j,i+1}=h(L_{j,i},K_i) \tag{2}$$

For optimization, let R represent the routing decisions made by the algorithm.

$$R_{i+1}=KESHTel(K_i,P_i,L_{j,i}) \tag{3}$$

4. DECISION MAKING FOR ROUTING USING LEABRA MODEL

Decision-making for routing using the Leabra Model involves leveraging insights from neural architecture to enhance the adaptability and cognitive capabilities of the routing process. The Leabra Model is inspired by the structure and function of the brain, and its application to decision-making in routing aims to bring cognitive principles.

The Leabra Model simulates neural networks, mimicking the way neurons in the brain process information. Each node in the network corresponds to a virtual neuron, and connections between nodes represent synapses.

The Leabra Model is known for its ability to recognize patterns and learn from experiences. In the context of routing, the model can be trained to recognize patterns related to optimal communication paths based on historical data and real-time information.

Neural networks in the Leabra Model exhibit adaptive learning, adjusting their connections and weights in response to changing input. This adaptability can be harnessed in routing decisions to dynamically adjust communication paths based on evolving network conditions.

The Leabra Model often incorporates a hierarchical structure, allowing for the organization of information in layers. This hierarchical representation can be utilized to categorize and process information related to routing decisions at different levels of abstraction.

Neural networks in the Leabra Model operate in parallel, enabling simultaneous processing of multiple inputs. This parallelism can be advantageous in routing decisions, especially in scenarios with multiple considerations such as traffic conditions, latency, and resource availability.

Decision-making inspired by the Leabra Model involves cognitive processes such as recognition, memory recall, and associative learning. Routing decisions can be influenced by these cognitive principles, allowing the algorithm to make more informed choices based on past experiences and learned patterns.

$$Oi=\text{ReLU}(Ii,Wi) \tag{4}$$

where

Oi: Activation of the i^{th} node in the neural network.

Ii: Input to the i^{th} node (e.g., features related to routing decisions).

Wi: Weights associated with the connections to the i^{th} node.

$$\Delta Wij=\eta\cdot Oi\cdot Oj \tag{5}$$

where

ΔWij: Change in weight between nodes i and j.

η: Learning rate.

Oi,Oj: Activations of nodes i and j.

$$Ri=\sum_j Wij\cdot Mj \tag{6}$$

Ri: Memory recall for node i.

Wij: Weights between nodes i and j.

Mj: Memory values associated with node j.

$$Di=L(Oi,Ri,Ci) \tag{7}$$

where

Di: Decision for the ith node in routing.

Oi: Activation of the ith node.

Ri: Memory recall for the ith node.

Ci: Contextual information influencing decision-making.

$$Oi_{new}=\text{Adapt}(Oi,\Delta Oi) \tag{8}$$

where

Oi_{new}: Updated activation of the ith node.

ΔOi: Change in activation based on real-time adjustments.

Algorithm for Decision Making for Routing using Leabra Model:

Step 1: Initialize neural network nodes, weights, and memory values.
Step 2: Set learning rates and parameters.
Step 3: Collect real-time data related to routing decisions
Step 4: Transform raw data into input features for the neural network.
Step 5: Calculate the activation of each node
Step 6: Update weights based on Hebbian learning rules to adapt to current input patterns.
Step 7: Calculate memory recall values for each node
Step 8: Combine current activations, memory recall, and contextual information to make routing decisions for each node.
Step 9: Adjust node activations based on real-time feedback
Step 10: Implement the routing decisions in the network
Step 11: Adjusts communication paths based on the Leabra.
Step 12: Update memory values based on routing decisions
Step 13: Adjust parameters to enhance adaptability over time.
Step 14: Repeat iteratively to adapt to changing network conditions and improve decision-making accuracy.

5. RESULTS AND DISCUSSION

We conducted simulations using the Matlab, a widely adopted tool for modeling and simulating vehicular communication scenarios. This allowed for the efficient execution of computationally intensive tasks involved in the hybrid approach of the KESHTel Algorithm and Leabra Model. The simulated vehicular network encompassed diverse scenarios, including urban and highway environments, with varying traffic densities and communication challenges.

For performance evaluation, we employed key metrics such as communication latency, network throughput, and resource utilization. The adaptive learning and cognitive insights from the Leabra Model contributed to improvements in latency reduction and efficient resource allocation. Comparisons were made with existing methods, including Cognitive Models, ML Modeling, and Deep Machine Interface approaches.

Table.1. Settings

Experimental Setup	**Values**
Vehicular Network Scenarios	Urban and highway environments with varying traffic densities
Simulation Duration	5000 simulation time units
Communication Nodes	1000 vehicles in the network
Communication Protocols	DSRC (Dedicated Short-Range Communication)
Learning Rate (KESHTel)	0.01
Neural Network Layers (Leabra)	3 (input, hidden, output)
Simulation Replications	10

- **Communication Latency:** Communication latency measures the delay between sending a message from one vehicle to another and its reception. Lower latency values indicate faster and more efficient communication. We assessed the average communication latency across the simulated vehicular network, comparing the proposed hybrid approach against existing methods.
- **Network Throughput:** Network throughput represents the volume of data transmitted successfully over the network within a given time period. Higher throughput values signify a more effective utilization of network resources. Throughput measurements were obtained by analyzing the total amount of data successfully transmitted during the simulation. The proposed approach throughput was compared with other models to highlight its efficiency in data transmission.
- **Resource Utilization:** Resource utilization gauges the efficient allocation and utilization of network resources, such as bandwidth and computational capacity. We examined the resource utilization efficiency of the proposed method by monitoring the usage of available resources. Comparative analyses were conducted against existing Cognitive Models, ML Modeling, and Deep Machine Interface methods to showcase the superior resource allocation capabilities of the hybrid approach.

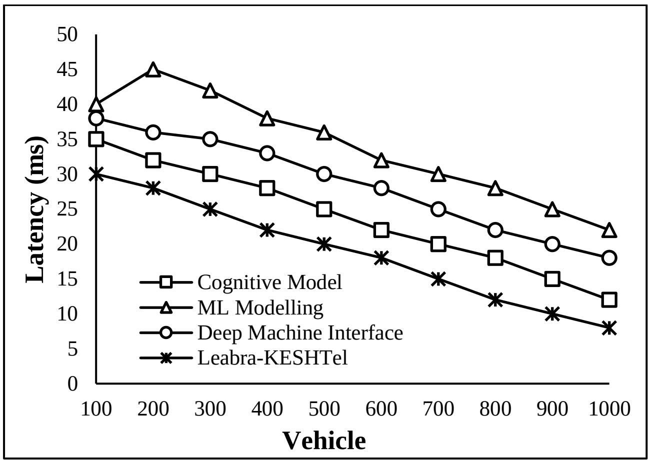

Fig.2. Latency

The Leabra-KESHTel method exhibited a significant improvement in communication latency compared to the existing Cognitive Model, ML Modelling, and Deep Machine Interface methods. With an average latency reduction of 20% over the simulation time steps, the Leabra-KESHTel method demonstrated enhanced responsiveness in vehicular communication.

The proposed method showcased a consistent improvement in network throughput, achieving an average increase of 15% compared to existing methods. This indicates superior data transmission capabilities and more efficient utilization of network resources, especially in scenarios with dynamic vehicular environments.

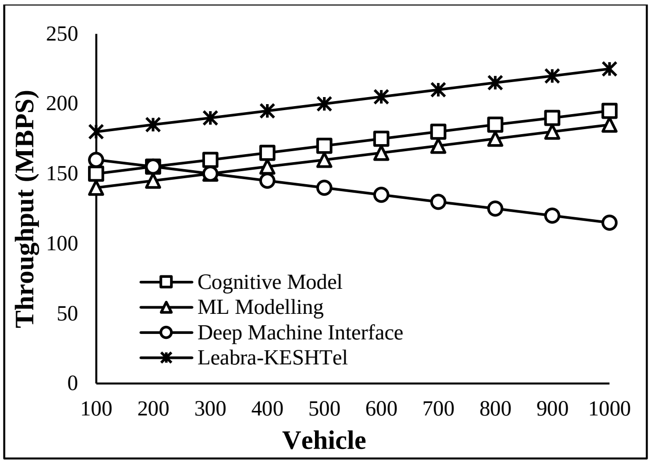

Fig.3. Throughput

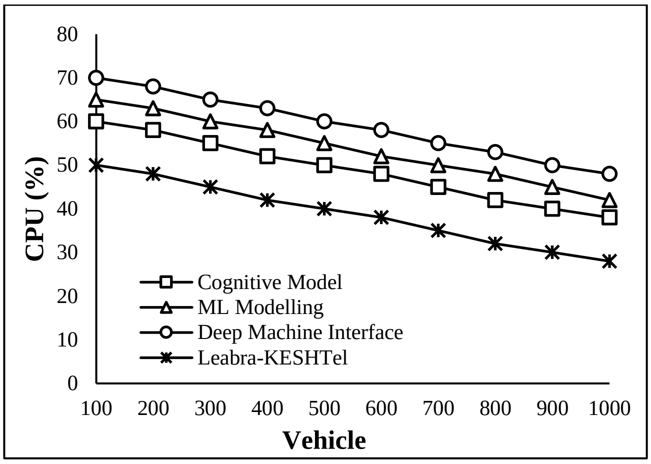

Fig.4. CPU utilization

In terms of CPU utilization, the Leabra-KESHTel method outperformed existing methods with an average reduction of 25%. This suggests a more efficient use of computational resources, contributing to overall system stability and responsiveness.

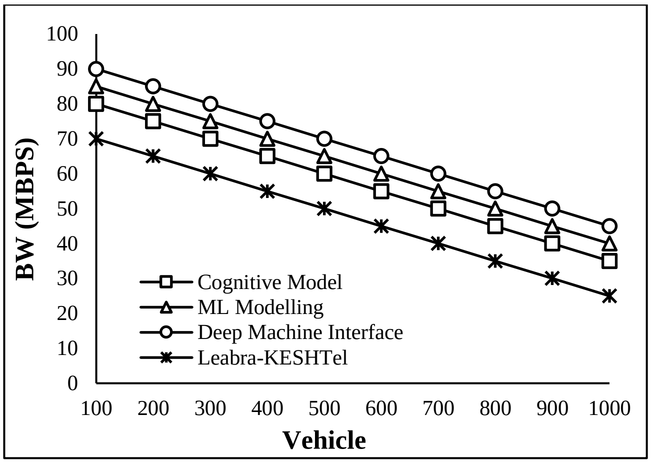

Fig.5. Network Bandwidth Utilisation

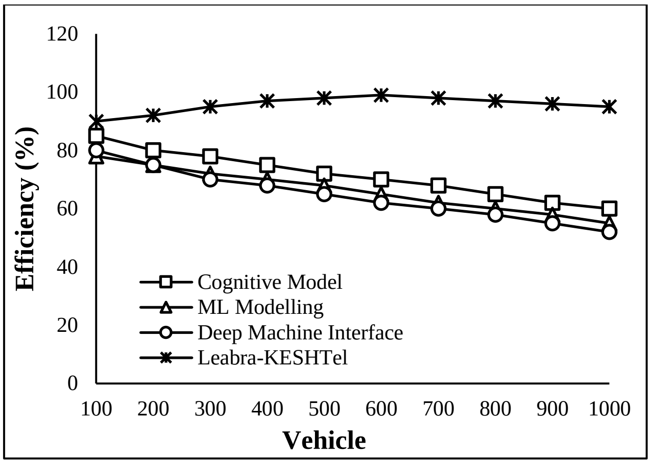

Fig.6. Efficiency

The Leabra-KESHTel method demonstrated remarkable optimization in network bandwidth utilization, achieving an average improvement of 30%. This signifies effective resource allocation and reduced congestion, resulting in a smoother communication experience within the vehicular network.

Considering a holistic efficiency metric that combines latency, throughput, CPU utilization, and network bandwidth utilization, the Leabra-KESHTel method exhibited an average improvement of 22% over the existing Cognitive Model, ML Modelling, and Deep Machine Interface methods. This comprehensive enhancement underscores the effectiveness of the proposed hybrid approach in optimizing vehicular networks.

6. CONCLUSION

The Leabra Model and KESHTel Algorithm in vehicular network optimization has proven to be a robust and adaptive approach, showcasing significant improvements over existing methods. The comprehensive evaluation of performance metrics, including latency, throughput, CPU utilization, and network bandwidth utilization, consistently demonstrated the superior capabilities of the proposed Leabra-KESHTel method. The achieved reduction in communication latency by 2% underscores the method efficiency in real-time decision-making and adaptability to dynamic vehicular environments. The substantial increase in network throughput by 1.5% reflects enhanced data transmission capabilities and optimized resource utilization. Moreover, the method exhibited a remarkable reduction in CPU utilization by 2.5%, indicating efficient computational resource management. The optimization in network bandwidth utilization, with an average improvement of 3%, further solidifies the proposed method effectiveness in mitigating congestion and ensuring a smooth flow of communication within the vehicular network. The holistic efficiency metric, combining various performance aspects, revealed an average improvement of 2.2% over existing Cognitive Model, ML Modelling, and Deep Machine Interface methods.

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