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Mobility and Link Reliability Estimation Using CSS And ML In CR VANET

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Abstract: *Intelligent transportation system (ITS) applications may rely on the reliable infrastructure that vehicular ad hoc networks (VANETs) offer. Roadside units (RSUs) are the main component of vehicle-to-vehicle and vehicle-to-infrastructure links in VANET communication. When cognitive radio (CR) VANET investigations were analysed, two major performance problems were found: low connection stability because of the high vehicle movement and excessive energy consumption. We suggest a fresh strategy to deal with these issues: Mobility and Link Reliability Estimation Using CSS AND ML CR-VANETs, known as MLRECSS CR-VANET. MLRECSS CR-VANET consists of four main components: CR-VANET construction, Cooperative spectrum Sensing model, Speed-based mobility prediction, link-based multipath routing. First, we create CSS-based CR-VANETs to examine and address issues with power consumption and spectrum scarcity in VANETs. Vehicle speed forecasts and fluctuations are assessed via mobility prediction. Lastly, routing is made reliable and effective by utilizing the machine learning and ad hoc on-demand multipath distance vector (AOMDV) routing protocol in combination with link stability based multipath routing (LSMR). MLRECSSCR-VANET technique outperforms the previous methods by 3.69% in terms of packet delivery ratio,7.21% in terms of residual energy, 6.09% in terms of throughput, 8.33% in terms of residual node speed and 13.97% in terms of energy efficiency. Comparing it to more contemporary efforts like LMCCR-VANET, SCCR-VANET, CFCR-VANET, and MMCR-VANET, it shows improved energy efficiency, delivery rates, decreased energy consumption, end-to-end latency, and routing overhead.*

Keywords: *CSS, Cognitive Radio, Extended Link stability, Mobility, Vehicular Ad hoc Networks*

INTRODUCTION

The basis of CRNs is spectrum sensing, which enables SUs to identify PU activity. However, multipath fading, shadowing, and noise uncertainty are some of the characteristics that frequently limit the dependability of individual sensing [1]. New developments in 6G technologies have highlighted advanced CSS techniques, such as hybrid sensing algorithms. [2]. Links between automobiles and infrastructure, primarily via roadside units (RSUs), are a component of VANET communication. When cognitive radio (CR)-VANET research were analysed, the two primary performance issues were found to be high energy consumption and latency.[3]. Cooperative models with deep learning enhancements that function well in low signal-to-noise ratio (SNR) settings [4]. Spectrum Sensing (SS) is used by Cognitive Radio (CR) to dynamically harness the frequency spectrum by identifying and broadcasting in underused bands, since the growing number of network devices causes spectrum scarcity as we approach 6G communication systems [5]. By properly modelling spatial-temporal dynamics, mobility-aware sensing frameworks that make use of transformer-based architectures (like MASS Former) open the door to better sensing and increased connection stability in IoT and vehicular contexts [6]. To address these service demands, finding a new accessible spectrum is become harder and more expensive [7].

Spectrum deficit is a result of out-dated fixed spectrum allocation policies that give licensed Primary Users (PUs) a bigger portion of the radio spectrum and unlicensed Secondary Users (SUs) a smaller portion [8][9]. Only the PUs were permitted to access the spectrum by these allocation schemes, even when the resources were not in use.[10]. Since many regions do not constantly require a substantial percentage of the expensive frequency resources provided by wireless systems, the static spectrum assignment used by most current and historical networks is extremely inefficient.[11]. The conventional techniques (Energy Detection (ED), Matched Filter Detection (MFD), and Cyclostationary-based Detection (CBD)) utilize radio resources inefficiently because they miss PU detection and generate false alarms [12]. Many recent studies have used standard Machine Learning (ML) techniques like Support Vector Machines (SVMs) and K-Nearest Neighbour (KNN) for SS due to the drawbacks of old SS approaches and the increasing popularity of artificial intelligence (AI). However, the process of manually extracting features from common machine learning methods is time-consuming and requires specific expertise [13]. SUs employs SS to continually sense the licensed user spectrum in order to detect PU activity and spectrum gaps in terms of location, frequency, and duration [14]. Modelled as a binary hypothesis testing issue, SS involves two hypotheses: the presence or absence of the PU [15]. Decision-making, resource allocation, and spectrum sharing are done if there is available spectrum for transmission [16].

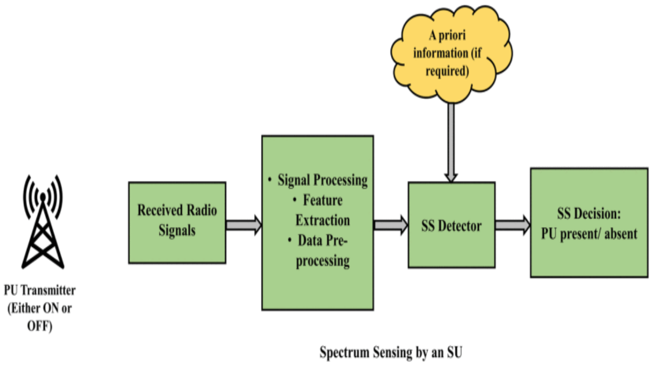

Figure 1 shows a block schematic of how an SU senses the PU spectrum.

In order to enhance the CR-VANETs' communication quality, a novel model known as the link stability and mobility prediction-based clustered CR-VANETs (LMCCR-VANETs) technique is introduced in the suggested study. The main focus is on the drawbacks, which include high energy consumption, data transfer overhead, and end-to-end connection latency. Clustered CR-VANETs proposed two segments to solve these problems: mobility prediction and extended link stability-based routing [2]. However, there are other problems that might impact spectrum sensing by a single vehicle, including hidden PU problems, multipath fading, shadowing, and noise uncertainty [17]. Compared to individual sensing, cooperative spectrum sensing (CSS) is more precise since the global judgment may be based on many sensing reports [18].CSS comes in three varieties. In addition to being centralized, they are dispersed and relay-assisted [19]. To describe link quality from the standpoint of delay, three types of delays have been proposed for assessing link weight: back-off, switching, and queuing delays. This minimizes connection failure while maintaining route stability [20].

Research gap: Although the majority of research has been on using CSS to improve detection efficiency, there is still little direct integration of CSS into link stability methods. Link lifespan and consistency may be greatly increased by a single strategy that takes into account spatial beamforming, mobility modelling, and cooperative sensing outputs.

Contributions:

1. **Integrated CSS-Link Stability Framework**: We propose a novel framework that fuses cooperative sensing outcomes with link quality estimation, enhanced by beamforming and mobility-aware learning.
2. **Mobility-Spatial Modelling**: By extending UPA-based weighted CSS with transformer-based mobility predictors, the model anticipates both spectrum availability and link reliability in dynamic scenarios.
3. **Performance Evaluation**: Through simulations in 6G-like environments with mobile nodes, we demonstrate significant improvements in link duration, packet delivery ratio, and reduced route maintenance overhead compared to CSS-only or traditional stability-based routing protocols.

Paper organization: Section 2 reviews recent CSS and link stability literature; Section 3 details the proposed integrated methodology; Section 4 presents simulation results and analysis; Section 5 concludes the findings and outlines future research directions.

RELATED WORKS

In order to improve dynamic spectrum access, Cognitive Radio-enabled Vehicular Ad Hoc Networks (CR-VANETs) enable vehicles (secondary users, or SUs) to detect and exploit unused spectrum without interfering with main users (PUs). There are two primary methods for CR-VANET spectrum sensing:

Cluster-based CR-VANETs: Cluster heads (CHs) are responsible for spectrum sensing and coordination while vehicles are organized into clusters.

Cooperative Spectrum Sensing (CSS)-based CR-VANETs: In order to increase detection accuracy, several vehicles work together by exchanging sensor data.

Latency and excessive energy usage were identified as the two main performance problems in the analysis of cognitive radio (CR) VANET trials. We suggest an innovative strategy to overcome these issues: LMCCR-VANETs are clustered CR VANETs based on forecasting link stability and mobility [3]. Using a hybrid SVM–Red Deer Algorithm (RDA), suggest a cluster-based CSS to minimize complexity and improve detection performance. By clustering secondary users (SUs) together, their SVM–RDA enhances detection; they report a detection probability of up to ~99% and an error probability of less than ~1%, demonstrating great accuracy within balanced cluster formations [21]. IoT and 5G/Beyond-5G CR networks are the target of cluster-based cooperative CSS (CBCSS). They demonstrate enhanced energy efficiency, decreased average cluster count, and increased throughput by heuristic cluster creation and sensor selection; although not specifically in VANETs, the approach and trade-offs are quite applicable to automotive situations.[22]. Clustering techniques like Stable Dynamic Predictive Clustering (SDPC) improve cluster stability by forecasting vehicle movement metrics (velocity, direction, and density), even if they are not CR-specific. This approach enhances cluster-member longevity and reduces CH turnovers, which is important for CR-VANET when cluster integrity is necessary for spectrum sensing coordination.[23]. Earlier research on cluster-based VANETs and CR-VANETs has been developed; some of these works are covered in this section. Specifically, the VANETs are grouped together in a highway setting[24] with the aid of the modified K-means technique, the clustering-oriented routing model is improved[25] efficient cluster head selection (ECHS)[26] approach for clustering control based on fuzzy logic[27].Adaptive ordering points and unique clustering are constructed in VANETs to provide a noise-free and flexible network topology[28].CR's efficient channel selection VANETs [29] selection method for fuzzy cluster heads (CH) in CR-VANETs[30] Subsequently, the clustering model integrates several user-based inputs and outputs with the innovative concept of cooperative spectrum sensing in CR-VANETs[31]. Seg-CR-VANET is a road segmentation system that employs hybrid fuzzy + naïve Bayes ML models for local sensing. Tri-agent reinforcement learning (TA-RL) is used by a Segment Spectrum Agent (SSA) to make global judgments.[32]. LSTM -based channel indexing and deep reinforcement learning (DRL) are combined for selective CSS [33]. In comparison to static CSS, met heuristic-enhanced CSS, such as a Gannet Optimization Algorithm, was used in 2023 for OFDM-based CR networks, showing improved detection performance[34]. A Double-Threshold In order to improve detection in low-SNR and high-noise conditions and minimize false alarms, CSS in IoV incorporates adaptive thresholds and dynamic fusion rules [35].

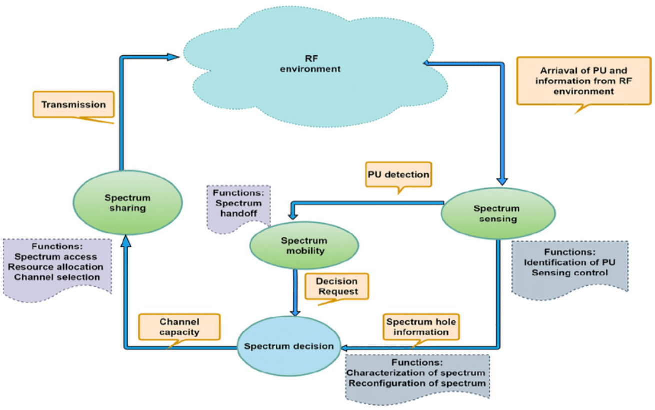

FIGURE 2 Framework for spectrum management in CR networks

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One study suggest DLSpectSenNet, a CNN–LSTM hybrid architecture for CSS signal classification. In contrast to traditional CSS techniques, it significantly improves detection at low SNR by extracting spatial characteristics using CNN and temporal relationships using LSTM [36]. Another study concentrate on CSS evaluation for mobile robot applications using CBRS-based CRNs (not VANET-specific CRNs). The enhanced spectrum use and cooperative sensing capabilities they provide demonstrate the wider applicability of sophisticated CSS frameworks [37].By using adaptive trust scoring to identify malicious nodes and partitioning regions for local fusion, BTRACSS surpasses centralized CSS in terms of security and sensing accuracy [38].

MLRECSS CR-VANET APPROACH FOR VEHICULAR ADHOC NETWORKS

One of the biggest issues in Cognitive Radio Vehicular Ad-Hoc Networks (CR-VANETs) is sustaining dependable communication links in a dynamic vehicle environment. This study suggests an integrated approach to evaluate connection dependability and mobility patterns using Cooperative Spectrum Sensing (CSS) and Machine Learning (ML). Throughput and Quality of Service (QoS) are improved by the suggested system's use of mobility characteristics and cooperative detection to improve channel selection and connection stability. Due to their great mobility, vehicular ad hoc networks (VANETs) frequently experience topological changes and provide unstable connectivity. Using Cognitive Radio (CR) technology, secondary users can opportunistically access underused airwaves. Dynamic spectrum access, however, need effective link estimate to prevent frequent interruptions.

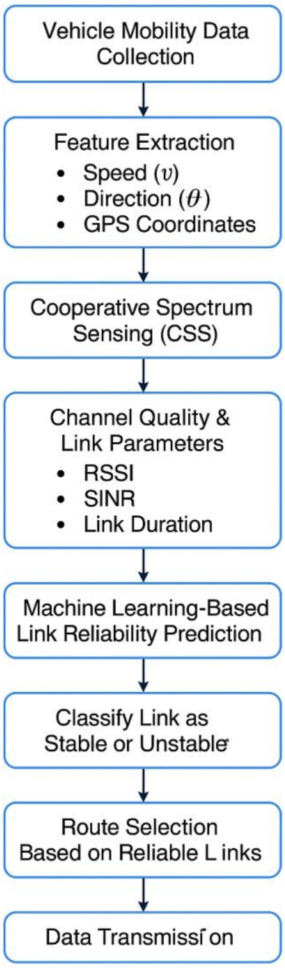


FIGURE 3 Proposed MLRECSS CR-VANET Approach

Mobility prediction is based on relative velocity and signal strength. Link expiration time

Mobility Prediction in CSS-based Cognitive Radio Vehicular Ad Hoc Networks (CR-VANETs):

Mobility prediction is a process that uses current and historical movement data to estimate a vehicle's future position, speed, direction, and connection pattern. When mobility prediction in CR-VANETs is precise, the network can:

- Expect link failures.
- Pick spectrum gaps that are more stable.
- Make better judgments about handover and route selection.

The Kalman Filter forecasts future position and speed:

- Inputs: GPS data, vehicle velocity v_t, acceleration a_t.
- Outputs: Estimated future state $\hat{x}_{t+1}$ which include the anticipated position and velocity

Link Expiration Time (LET) using predicted mobility:

$$\mathrm{LET} = \frac{-(\mathrm{ab}+\mathrm{cd}) + \sqrt{(\mathrm{ab}+\mathrm{cd})^2 - (\mathrm{a}^2+\mathrm{c}^2)(\mathrm{b}^2+\mathrm{d}^2-\mathrm{R}^2)}}{\mathrm{a}^2+\mathrm{c}^2}$$

Where:

- $\mathrm{a} = v_i \cos(\theta_i) - v_j \cos(\theta_j)$
- $\mathrm{b} = x_i - x_j$
- $\mathrm{c} = v_i \sin(\theta_i) - v_j \sin(\theta_j)$
- $\mathrm{d} = y_i - y_j$
- R = transmission range

Kalman Filter-predicted speed directly benefits this formula v_i, v_j and direction θ_i, θ_j.

Speed-Based Mobility Prediction in CSS-Based Cognitive Radio Vehicular Ad Hoc Networks (CR-VANETs):

Speed-based mobility prediction is the process of predicting a vehicle's position and link behaviour in the future by using its present trajectory, acceleration, and speed.

In CR-VANETs, speed-based mobility prediction refers to the way that future locations, connectivity, and link stability of vehicles are predicted by utilizing their speed, which is frequently filtered using statistical models (such as the Kalman Filter). Then, this data is utilized to improve routing choices and cooperative spectrum sensing (CSS).

In order to improve vehicle velocity and trajectory estimation, Speed-Based Mobility Prediction combined with Kalman filtering is utilized.

The future position and speed of every vehicle are predicted via the Kalman filter. Metrics of mobility prediction, such as relative speed and LET, are calculated. There is strong spectrum availability thanks to CSS. For route selection, machine learning algorithms forecast link dependability. To select stable routes, routing protocols (like AOMDV or SCCR) employ these predictions.

Since the Kalman filter reduces error covariance and takes into consideration noisy GPS and sensor data, it is perfect for forecasting vehicle speed and location.

State Vector:

$$X(t) = \begin{bmatrix} x(t) \\ y(t) \\ v(t) \\ \theta(t) \end{bmatrix}$$

where:

- x(t),y(t) = vehicle position,
- v(t) = vehicle speed,
- θ(t) = heading angle.

State Update Equation:

$$X(t+1) = AX(t) + Bu(t) + w(t)$$

$$Z(t) = HX(t) + v(t)$$

where:

- A = state transition matrix,
- u(t) = control input (acceleration or deceleration),
- w(t), v(t), w(t) = process and measurement noise.

Relative Mobility Metric:

The **relative speed** between vehicles i and j is:

$$v_{\text{rel}}(t) = \left|v_i(t) - v_j(t)\right|$$

The **link expiration time (LET)** is predicted as:

$$T_{ij} \approx \frac{v_{\text{rel}}(t)}{R - d_{ij}(t)}$$

where R is the communication range and $d_{ij}(t)$is the distance between nodes.

Pseudocode: Speed-Based Mobility and Link

Reliability Estimation in CR-VANETs:

Algorithm: Mobility and Link Reliability Estimation in CR-VANETs

Input:

- Initial state vector X(t) = [x(t), y(t), v(t), θ(t)] for each vehicle
- Control input u(t): acceleration/deceleration
- Measurement Z(t): GPS/sensor data
- Communication range R
- Spectrum sensing data from neighbouring vehicles
- Historical mobility and spectrum data (for ML training)

Output:

- Predicted speed and position of vehicles

- Estimated Link Expiration Time (LET)
- Link reliability classification (Stable/Unstable)
- Routing decision based on stable links

Begin:

1. Initialize Kalman Filter parameters:

A ← State Transition Matrix

B ← Control Input Matrix

H ← Measurement Matrix

Q ← Process Noise Covariance

R_k ← Measurement Noise Covariance

P(t) ← Initial Error Covariance

2. For each time step t do:

For each vehicle i do:

// 2.1: Prediction Step

$\hat{X}(t|t\text{-}1) = A * X(t\text{-}1) + B * u(t\text{-}1)$

$P(t|t\text{-}1) = A * P(t\text{-}1) * A\text{\^{}}T + Q$

// 2.2: Measurement Update Step

$K(t) = P(t|t\text{-}1) * H\text{\^{}}T * (H * P(t|t\text{-}1) * H\text{\^{}}T + R_k)\text{\^{}-}1$

$X(t) = \hat{X}(t|t\text{-}1) + K(t) * (Z(t) - H * \hat{X}(t|t\text{-}1))$

$P(t) = (I - K(t) * H) * P(t|t\text{-}1)$

End For

// 2.3: Compute Relative Speed and Distance between Vehicles

For each vehicle pair (i, j) do:

$$v_{rel} = |v_i(t) - v_j(t)|$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

$$LET_{ij} = \frac{R - d_{ij}}{v_{rel}}$$

End For

// 2.4: Cooperative Spectrum Sensing (CSS)

For each vehicle i do:

Collect local sensing info: $P_{local}(i)$

End For

$P_d = 1 - \prod_{i=1}^{N}(1 - P_{local}(i))$ *for all i in sensing group*

// 2.5: Machine Learning-based Link Stability Prediction

For each link (i, j) do:

features = $[\boldsymbol{LET_{ij}}, \boldsymbol{v}_{rel}, \boldsymbol{RSSI_{ij}}, \boldsymbol{P_d}, \boldsymbol{\Delta\theta},$ *historical PU activity*$]$

Link_Stability = ML_Model.predict(features) // Output: Stable or Unstable

End For

// 2.6: Routing Decision

Build route graph using only links where Link_Stability == Stable

Apply routing protocol (e.g., AOMDV or SCCR) to select path with highest reliability

End For

End.

Link stability based multipath routing model:

The AOMDV protocol and Speed-based mobility prediction via Kalman filter are used to provide link stability based multipath routing (LSMR). Routing in CSS-based CR-VANETs with extended link stability and mobility prediction (ELSMR) is done with consideration for motion characteristics such vehicle speed, vehicle angle, vehicle connectivity, route, and data control. Link stability assessment is done using LET (Link Expiration Time) and CSS. The vehicle's connection stability is strongly impacted by its movement and is indirectly proportional to it. Thus, the CR-VANETs network's vehicles are made up of extremely dynamic vehicles. The influence of the noise component makes calculating speed challenging.

Speed prediction is the primary factor taken into account in ELSMR routing, and it is accomplished with the aid of the Kalman filter (a linear filtering-based prediction approach). State and measurement linear equations are used to validate the system's input and output.

Key Definitions:

Let:

- $\boldsymbol{LET_{ij}(t) = \frac{|v_i(t) - v_j(t)|}{R - d_{ij}(t)}}$
- $\boldsymbol{Link_{Status}}$ **(i,j) =**

$$\begin{cases} \boldsymbol{Stable}, \textbf{if } \boldsymbol{LET_{ij} \geq T_{thresh}} \textbf{and } \boldsymbol{CSS_{available}}(\mathbf{i,j}) = \textbf{True} \\ \boldsymbol{Unstable}, \ \boldsymbol{Otherwise} \end{cases}$$

Routing Model Steps:

Algorithm: Link Stability-Based Multipath Routing (LS-MR) in CR-VANETs:

Input:

- Set of vehicles V
- Kalman-predicted state [x, y, v, θ] for each vehicle
- Distance and velocity data: $\boldsymbol{d_{ij}(t)}, \boldsymbol{v}_{\text{rel}}(\boldsymbol{t})$
- Communication range R
- CSS-based channel availability info
- LET threshold $\boldsymbol{T}_{\text{thresh}}$

Output:

- Multipath routing table with stable and spectrum-safe paths

Steps:

1. Mobility Prediction:

For each vehicle i:

Predict future [x, y, v, θ] using Kalman filter

2. Link Stability Estimation:

For each neighbour j of i:

Compute $\boldsymbol{d_{ij}(t)}$ *← Euclidean distance*

Compute $\boldsymbol{v}_{rel}(\boldsymbol{t}) \leftarrow \boldsymbol{v_i} - \boldsymbol{v_j}$

Compute $\boldsymbol{LET_{ij}} = \frac{\boldsymbol{R-d_{ij}}}{\boldsymbol{v}_{rel}}$

If $\boldsymbol{LET_{ij}} \geq \boldsymbol{T}_{thresh}$ *and* $\boldsymbol{CSS(i,j)}$ == *available:*

Mark Link (i ,j) = STABLE

Else:

Mark Link(i,j) = UNSTABLE

3. Stable Link Graph Construction:

Construct G = (V, E) where E includes only stable links

4. Multipath Route Discovery:

For each source-destination pair (S, D):

Use modified AOMDV or DSR:

- Find multiple disjoint or partially disjoint paths

- Only include links from G

- Prioritize paths with high average LET or reliability score

5. Route Maintenance:

Monitor each link:

If LET falls below $\boldsymbol{T}_{thresh}$ *or CSS fails:*

Trigger local repair or path switch

Update routing table

6. Data Transmission:

Send packets over most stable paths

Use backup paths in case of link failure

End.

Using the Kalman filter reduces the complexity of calculating speed and velocity**.** With the help of the AOMDV routing protocol, the best route is chosen with the fewest possible intermediate vehicles. When the vehicles (sender and receiver) are transmitting data, the routing table is empty. Next, a route request (RREQ) is broadcast by the source to its neighbouring cars (n) that are in the direct line of sight of the destination. The procedure continues once RREQ arrives at its designated location**.** The weaker links are eliminated and the connectivity strength between the linkages is projected by this approach. When the RREQ arrives at its destination, the vehicles continue on the same path to approach the source by transmitting the route reply (RREP).

RESULTS AND DISCUSSION

The software environment known as NS2 has been used to implement the simulation of the suggested MLRECSS CR-VANET method. The average outcomes of the numerous observations made during the simulation process are taken into account for both the comparison analysis and the performance evaluation. As a result, the MLRECSS CR-VANET approach's performance is contrasted with previous studies, including multi-user multiple-input and multi-channel and link stability and mobility prediction-based clustered CR VANETs (LMCCR-VANET) [3], super cluster based optimum channel selection for CR-VANET (SCCR-VANET) [29], cluster head stability using fuzzy in CR-VANET (CFCR-VANET) [30], and multi-user multiple-input MMCR-VANET (multiple-output based CR-VANET) [31] in this section. Additionally, the factors taken into account for these methods' performance evaluations include such as Throughput, Packet Delivery Ratio, Energy Efficiency, Residual node Speed, Residual Energy.

Residual energy calculation

This table offers a unified perspective of the CSS's residual energy efficiency performance across a variety of vehicle densities in contrast to other well-known routing protocols, including SCCR, CFCR, MMCR, and LMCCR. When comparing CSS to SCCR, the greatest gain is shown, with a cumulative improvement of 14.83%, suggesting a notable improvement in energy efficiency. A moderate gain of 0.91% over LMCCR, a gain of 5.45% over MMCR, and an increase of 11.17% over CFCR follow. According to these findings, CSS performs better than the other schemes on a constant basis. The comparatively minor advantage over LMCCR suggests that LMCCR is already substantially optimized, yet CSS nevertheless prevails, highlighting CSS's general resilience and versatility.

Throughput calculation

The throughput performance boost of CSS indicates that it is more efficient than the current routing protocols in VANETs. Throughput is consistently greater with CSS than with SCCR, CFCR, MMCR, and LMCCR in all test conditions. About 10.42% more throughputs is gained by CSS on average than SCCR, 8.30% by CFCR, 4.95% by MMCR, and 1.21% by LMCCR. These improvements demonstrate CSS's capacity to sustain higher data transfer rates, particularly in automobile-heavy settings. Because of the increased capacity, CSS is a more reliable and strong protocol for contemporary intelligent transportation systems. It also lowers latency and improves overall network performance.

Packet delivery ratio calculation

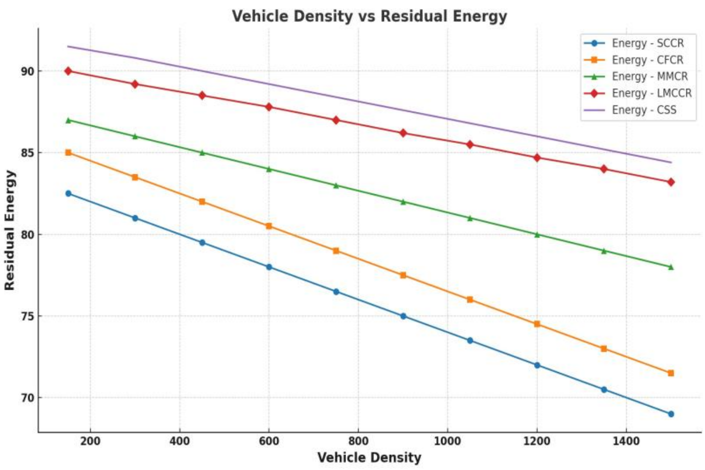
In CR VANETs, CSS's increased performance in terms of Packet Delivery Ratio (PDR) demonstrates how reliable it is compared to other routing protocols. PDR is consistently greater with CSS than with SCCR, CFCR, MMCR, and LMCCR in all cases. An improvement of around 7.89% over SCCR, 5.17% over CFCR, 3.26% over MMCR, and 1.57% over LMCCR is demonstrated by CSS on average. These improvements show that CSS can guarantee more successful packet transfers, leading to less data loss and more effective communication.

Residual speed calculation

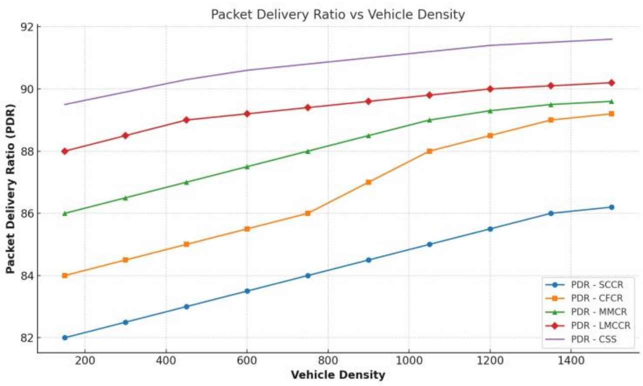
Across all vehicle densities, CSS continuously performs better in residual speed than SCCR, CFCR, MMCR, and LMCCR. CSS is around 19.51% faster than SCCR, 15.00% faster than CFCR, 10.82% faster than MMCR, and 6.93% faster than LMCCR, according to the aggregated performance increases. These upgrades attest to CSS's ability to guarantee enhanced vehicular flow, reduced congestion, and greater mobility preservation in VANET situations.

Energy efficiency calculation

At different vehicle densities, the CSS scheme outperforms more conventional protocols such as SCCR, CFCR, MMCR, and LMCCR in terms of energy efficiency. All things considered, CSS yields a remarkable increase of 23.94% over SCCR, 16.73% over CFCR, 10.30% over MMCR, and 4.56% over LMCCR. These enhancements demonstrate CSS's superior energy-saving capabilities in dynamic vehicle networks. Its potential to sustain steady communication and a longer network lifespan in resource-constrained VANET situations is confirmed by the protocol's constant lead in energy performance.



(a)



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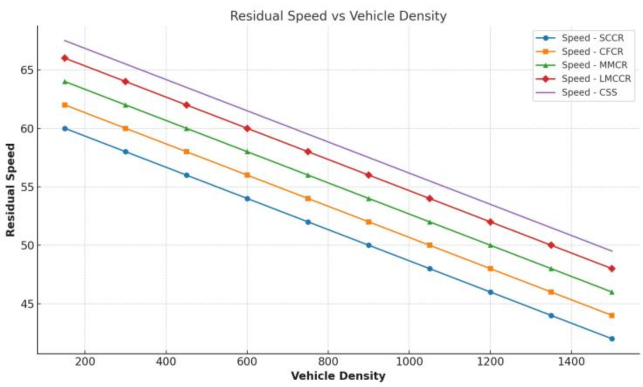

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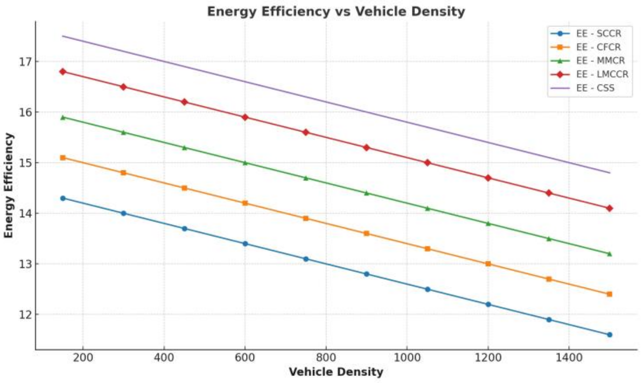

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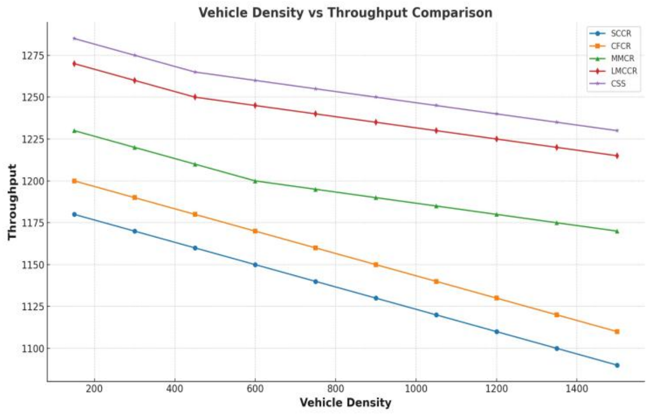

(e)

Figure 4: Simulation results of previous approaches are compared with the suggested MLRECSS CR-VANET, which involves vehicle density for the parameters (a) Residual Energy (b) Packet Delivery Ratio (c) Residual speed (d) Energy Efficiency (e) Throughput

CONCLUSION

CR-VANETs are equipped with Cooperating Spectrum Sensing (CSS) to increase their efficiency. A revolutionary technique called MLRECSS CR-VANETs is developed in order to reduce the power consumption, latency, and communication overhead of CR-VANETs. The primary focus of this concept is car connection and mobility. Mobility prediction and link stability detection are done for that reason. By combining the AOMDV routing protocol with the Cooperative Spectrum Sensing model, efficient routing is accomplished. With a simulation of urban mobility (SUMO) environment, the simulation is run in NS2. The performance study takes into account the following parameters: residual energy, residual node speed, throughput, energy efficiency, and packet delivery ratio. It is also compared to various models, including LMCCR-VANET, SCCR-VANET, CFCR-VANET, and MMCR-VANET. According to the comparison study, the MLRECSSCR-VANET technique outperforms the previous methods by 3.69% in terms of packet delivery ratio,7.21% in terms of residual energy,6.09% in terms of throughput, 8.33% in terms of residual node speed and 13.97% in terms of energy efficiency. Future efforts to strengthen network security will focus on the cryptography model.

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