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Neighbor predictive adaptive handoff algorithm for improving mobility management in VANETs

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ABSTRACT

A vehicular ad-hoc network (VANET) was employed in commercial, road-safety, and entertainment applications due to its accessibility. Applications and services were shared with the service providers (SP) over mobile nodes to any destination without special infrastructure. The mobility pattern of the nodes was independent, and the acceleration remained unpredictable, which led to service failures and information drop-outs. Resuming communication requires the flooding of additional control messages, which exploits the network resource in a shorter period. This paper introduces the neighbor predictive adaptive handoff (NPAH) algorithm for ensuring seamless communication, regardless of the application service time. NPAH discovers weak communication links in the service, which persist through the least resource dependent distance-based neighbor discovery. The selected neighbors are characterized by distance and minimum cost exploitation using the Q-learning technique. The process of learning decides the handoff of a vehicle based on storage utilization and cost factors. The results demonstrated the effectiveness of the NPAH algorithm by achieving less packet loss, shorter outage times, and improving the delivery factor.

1. Introduction

A group of vehicles interconnected through an on-demand fashion for information sharing constitutes a vehicular ad-hoc network (VANET). The components of a VANET architecture include on-board units (OBU), the vehicles, infrastructure systems, such as roadside units (RSU) or access points (AP), and wireless communication channels. The communication modes feasible in vehicular networks with these components are vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I). In addition to these conventional modes, a hybrid architecture combining V2V and V2I is popular for heterogeneous communications in vehicular networks.

The intrinsic vehicular attributes of speed and direction necessitate vehicles to change position and distance frequently. Therefore, the vehicle must continue to change its communication points [1] during the vehicle information transmission process. During handoff or handover, a vehicle blocks receiving services from its previously connected communication point and joins another for receiving services. More often, the vehicle joins a new communication using access points located in the direction towards where the vehicle is headed. VANETs, being the extended applications of mobile ad-hoc networks, discover new routes to the communication points at the time of handoff. The communicating vehicle instigates re-routing to discover new communication points located close by or further away [2–6]. If the communication point is located multiple hops away, then the communicating vehicle depends on its neighbors for routing. As the vehicles are autonomous, re-routing requires an additional delay. The quality of service requirement in VANETs relies on the performance of this handoff where data transmission must occur through shorter delay paths.

VANET services are classified as real-time and non-real-time applications. Real-time applications include localization systems and video calls, and non-real-time applications include messaging services and internet access. Handoff procedures developed for VANET must ensure seamless performance for supporting these applications. Due to the unpredictable velocity and direction of vehicles, handoff in VANETs is a demanding task [7–9].

VANET applications require the position of the moving vehicles to aid in precise end-user services. Conventional global positioning system (GPS) localization in VANET does not satisfy the position dependent applications due to availability issues and proximity of signal errors [10,11]. Localization, handoff, and communication management are the integrated blocks and challenges for mobility management (MM) in VANETs. With appropriate mobility management, the service demands of VANET applications can be satisfied by sustaining active and seamless communications, which

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can be achieved if the reconnection of the vehicle is successful with a new point of attachment (PoA) [12,13].

The contributions presented in this paper include the following:

- Designing a distance-based neighbor discovery method for identifying optimal routes to the base station (BS) to gain information access. Achieving optimality in determining routes to the BS improves reliability in communication by increasing the delivery factor of the network.
- Designing a Q-learning-based adaptive for selecting neighbors based on storage utilization and costs. This method aids non-destructive communication features post-handoff. This results in fewer outages with controlled delays.
- Performance analysis of the proposed NPAH through different metrics with a comparative study to prove the consistency of the handoff algorithm.

The remainder of the paper is organized as follows. Section 2 discusses the related works, and Section 3 describes the NPAH, the network model, and its methodology followed by the performance analysis with results in Section 4. Finally, future directions are presented in Section 5.

2. Related works

The authors in AlFarraj et al. [14] proposed a mobility-based handoff based on the angle of arrival (AoA) for ensuring seamless connectivity and minimizing packet loss in VANETs. This handoff predicted the relative direction of the vehicle [15] from which the present access point predicted the next communication point in this direction of travel. The network layer handoff was followed by the link layer handoff that ensured seamless communication between the vehicle and the infrastructure [16].

Moravejosharieh and Modares [17] analyzed the Proxy Mobile IPv6 (PMIPv6) Protocol for minimizing handoff latency and packet loss in VANETs. The gateways broadcasted communication information of the moving vehicles with respect to the point of attachments (PoAs) of the vehicles. The gateways assigned IP addresses to the vehicles, and the successor gateway acknowledged the vehicle with an information request message to approve its handoff. The position of the vehicles was updated using GPS in the vehicles. Address assignment and maintenance in this model increased overhead.

To improve accuracy and minimize delay over the Internet of vehicles' communications, the authors in Wang et al. [18] introduced the self-decision tree-based vertical handoff method. Built from the network configuration and the mobility pattern of the vehicles, a probability distribution selected the mode of communication. The feedback of the probability distribution handoff was analyzed to improve handoff accuracy and minimize delay.

The efficient proxy mobile IPv6 (E-PMIPv6)-based handoff in urban regions, introduced by Bi et al. [19], intended to improve communication stability for mobile users by ensuring Internet access was provided through stationary infrastructures and mobile users during the initial phase. In the handoff stage, connectivity was ensured by allocating optimal mobility management. This handoff scheme curtails packet loss by improving cache utilization.

Virtual soft handoff was introduced by Balachandran et al. [20] to address interference and capacity problems in the LTE uplink to improve end-user performance. The authors investigated the feasibility of incorporating resource blanking into the introduced handoff method for interference cancellation and avoidance.

A solution to resolve Quality of Experience (QoE) degradation in cognitive cellular networks was introduced in Piran et al. [21] using channel information and ranking index. The channels were assigned a ranking index by evaluating quality from the observed channel utilization information. A priority-based channel allocation that satisfied the application demand was designed to enhance the performance of the introduced handoff management scheme and improve channel utilization with higher video quality and shorter delays.

A combination of the Markov decision process (MDP) and the genetic algorithm (GA) [22] was applied to improve optimality in vertical handover channel selection. In an MDP, the QoS satisfying metrics were maximized, and GA was applied to minimize the cost function of the MDP. The uncertainties in GA were eliminated by using simulated annealing optimization to minimize the handoff frequency decision time.

Fast handover distributed mobility management (FDMM) [23] was introduced to minimize packet loss and latency and improve communication recovery time seen in Bi et al. [19] and Piran et al. [21]. The FDMM constructs bidirectional tunnels between the service provider and the mobile anchor to ensure timely communication after the handoff. FDMM operates in predictive and reactive communication modes to relay information between the mobile anchor and the access routers.

Yao et al. [24] analyzed predictive routing based on a hidden Markov model (PRHMM) to improve transmission in vehicle-to-everything V2X communications. This model observed the repetition degree of the vehicle to predict its future location to provide uninterrupted communication during handoff. This model also predicted the temporary routing path and packet delivery probability of the mobile destination to improve transmission performance.

Vertical handoff decision (VHH) was discussed in Hassoune et al. [25] to improve the performance of real-time vehicular applications on highways. VHH prevented redundant and frequent handoffs based on density, position, velocity, and jitter observed from the vehicles and communications. This VHH is developed for multimedia applications along highways to deliver better video quality.

In a multi-mobile node scenario, conventional DMM is not appropriate due to the generation of redundant messages by the increased node communication. To handle this problem, a Bursty multi-node handover scheme using partial DMM (BMH-DMM) was discussed in Huang et al. [26]. The mobile nodes were grouped based on location, and a limited set of control messages were exchanged, thereby minimizing overhead. This group messaging scheme enabled multiple mobile nodes to communicate simultaneously while minimizing redundancy and latency.

3. Neighbor predictive adaptive handoff for seamless VANET communication

3.1. Problem definition

Mobility management relies on localization and handoff processes common in VANETs to ensure seamless communication despite frequent vehicle movement. Mobility management was introduced in the past to concentrate on short-lived factors expected to serve the purpose for a prolonged period. Handoff occurring based on extinct factors results in non-optimal solutions at the time of neighbor reinforcement. This leads to stagnant handoff that trails behind application demands, which increases outage time, saturated handoffs, and packet loss in the network. The neighbor predictive adaptive handoff (NPAH) was constructed on a preference function, and the neighbor selection technique was based on Q-learning. The preference function was responsible for effective handoff triggering, and Q-learning-based neighbor selection chooses optimal neighbors with less re-routing procedures. During this handoff, the short-lived metrics were discarded, and the assessable metrics were relayed over varying network topologies following a recent update.

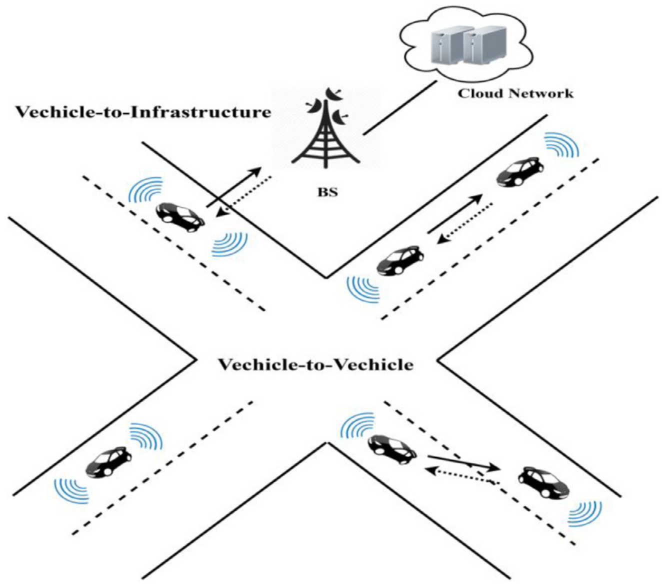

Fig. 1. The VANET model.

3.2. Network model

Fig. 1 illustrates the network model in which the vehicles communicate in V2V and V2I modes. The vehicles relay and request information between neighbors and the BS. The BS, connected to a cloud network for access, storage, and retrieval, is responsible for updating the global network information on request from the vehicles. The BS searches the cloud when replying to the queries generated by the vehicles. Each vehicle V is traveling at an acceleration a with independent direction vectors $(\overrightarrow{dv})$. The vehicles move and find a PoA in the direction of travel, $\overrightarrow{dv}$. If $\mathrm{R_v}$ is the communication range of a vehicle, then two vehicles represented as $\overrightarrow{dv(i,j)}$ are neighbors if $d(i,j) < R_v(i) \| R_v(j)$. The OBU in a vehicle is interfaced with miniature storage to maintain and forward incoming information. A conventional handoff process in a VANET is illustrated in Fig. 2.

3.3. NPAH methodology

The NPAH operates first with a distance-based neighbor discovery followed by Q-learning-based adaptive neighbor selection. The distance-based neighbor discovery stage is instigated by the vehicles participating in a communication process. Adaptive neighbor selection favors optimal vehicle selection at the time of re-routing before handoff. The first stage is responsible for ensuring reliability in service discovery and the second stage is responsible for minimizing latency and outages at the time of handoff.

3.3.1. Distance-based neighbor discovery

Distance-based neighbor discovery is used to favor new vehicles by provisioning optimal routes to the service providing BS. The active vehicle relies on its neighbors to reach the service providing BS. The dependent neighbors are either novice or experienced in the same network region. Novice vehicles expect minimum bandwidth exploitation and a short distance vehicle link to the BS. These two factors are unified by a preference function (f(np)) for neighbor selection to acquire services from the BS. The preference function minimizes inequality between the considered metrics through a min-max validation. The bandwidth utilization (b_u) of an experienced link l over k transmissions is estimated as

$$b_u = c_l \times \left[1 - \frac{\varphi_{tr} - \varphi_{tt}}{\varphi_{tt}}\right], \ \forall k \tag{1}$$

where c_l, φ_{tr}, and φ_{tt} are the link capacity, service reception, and transmission time, respectively. Bandwidth exploitation depends on the type of application requested by the vehicle. The bandwidth

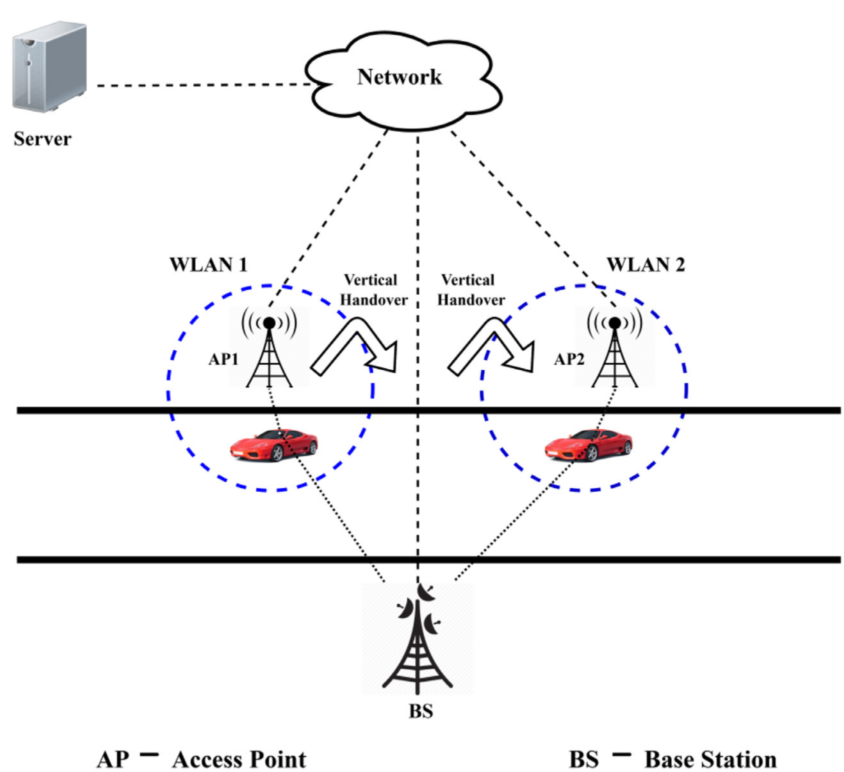

Fig. 2. A conventional handoff in a VANET.

of the link between a novice (V_n) and experienced (V_e) vehicle is ideal if it satisfies

$$b(\mathrm{link}(V_n, V_e)) = \min\{b_u(l)\},\ l \in \mathrm{link}(V_n,\ V_e) \quad (2)$$

Let p_v, p_v^*, and p_{BS} be the current and previous positions of a vehicle v and the position of the BS. Here, bandwidth is considered as a concave metric and link duration is estimated as an additive metric. Link duration is dependent on bandwidth purely, so bandwidth utilization is a concave metric. The distance between the vehicle and the BS is $d_{v,\,BS}$ at time t estimated by

$$d_{v,BS} = |p_v - p_{BS}| \quad (3)$$

where $p_v = p_v^* + a * t$.

Let the positions of two vehicles, i and j, be $p_i(x_i,\ y_i)$ and $p_j(x_j,\ y_j)$ with accelerations a_i and a_j, respectively. The change in distance at time t, $\Delta d(t)$ is estimated as

$$\Delta d(t) = \sqrt{(\Delta x_0 + \Delta a_i * \Delta t)^2 + \left(\Delta y_0 + \Delta a_j * \Delta t\right)^2} \quad (4)$$

where $\Delta x_0 = (x_i - x_j)$, $\Delta y_0 = (y_i - y_j)$, $\Delta a_i = a_i - a_i^*$, $\Delta a_j = a_j - a_j^*$, and $\Delta t = t - t^*$.

The link duration, $\mathrm{ld}(i,\ j)$, with respect to change in distance at a time t, is estimated with

$$\mathrm{ld}(i,\ j) = \frac{1}{\left(\Delta a_i^2 + \Delta a_j^2\right)} * \left(-\Delta x_0 \Delta a_i - \Delta y_0 \Delta a_j\right) \pm \sqrt{R_v^2\left(\Delta a_i^2 + \Delta a_j^2\right) - \left(\Delta x_0 \Delta a_j - \Delta y_0 \Delta a_i\right)^2} \quad (5)$$

where Δx_0 and Δy_0 are the initial positions of the vehicle with differential accelerations Δa_i and Δa_j of the vehicles i and j, and R_v is the range of the vehicle.

The preference function adds random weights to the inequality between the two metrics. The random weights are adjusted with respect to the vehicular density observed near the communication-demanding vehicle. The preference function is derived using

$$\mathrm{f(np)} = \max\{\omega_1 * b_u + \omega_2 * \mathrm{ld}(i,\ j) \quad (6)$$

where ω_1 and ω_2 are the adjustable weights of the considered metrics, and $\omega_1 + \omega_2 = 1,\ \omega_1 < \omega_2$. If ω_1 is higher than ω_2, then bandwidth utilization is given a maximum preference. The weight factors determine which considered factor needs preference. Depending upon the neighbor availability and service requirement, link stability is given higher preference. Therefore, the second weight is modeled to hold higher values than the bandwidth metric.

For a min-max formulation, Eq. (6) is revised as

$$\mathrm{f(np)} = \begin{cases} \min\,(b_u) \\ \max(\mathrm{ld}) \end{cases} = \begin{cases} \min\,(b_u) \cup \max(\mathrm{ld}(i,\ j)) \\ 0,\ \text{otherwise} \end{cases} \quad (7)$$

This min-max formulation balances two distinct factors for selecting an appropriate neighbor. Bandwidth and link are considered to ensure seamless communication for a prolonged time. The service requesting novice vehicle is broadcasted with the preference value of its neighbor, and from this, the vehicle with maximum preference is selected for initiating the communication session. The weak communication links are identified by improving the importance of link stability in Eq. (6). The links with less stability and active time will be discarded on evaluating the Eq. (6) resulting in prominent link availability. This improves the communication reliability with more seamless transmissions.

Theorem 1. *For a varying set of neighbors V_e or V_n, the handoff may not be constant,* $\mathrm{ld} \gg b_u(\Delta t)$.

Proof: Let σ_0 be the initial count of vehicles within the range of the novice vehicle. The wireless communication links between the vehicles cause interference due to a limited number of vehicles remaining connected. More precisely, the neighbors with higher *ld* remain connected over a change in time Δt. Therefore, it is mandatory to compute the number of neighbors connected (σ_n) with the novice vehicle using

$$\sigma_n(\Delta t) = \sum_{i=1}^{m} \rho_{i,n}^{d(i,n)}(\Delta t) \quad (8)$$

where $\rho_{i,n}^{d(i,n)}$ is the probability of a vehicle i being connected with the novice vehicle. The number of neighbors connected to a vehicle ensures the stability of communication as expected by the vehicle after the handoff. The connectivity of a vehicle changes due to different accelerations and communication time intervals. This factor makes it prominent to estimate the connected neighbors at any instance of time. The value of $b_u(\Delta t)$ is not negligible as the link duration factor is dependent on the available bandwidth. If the bandwidth is minimum or negligible, then desired communication rates cannot be achieved. Though selection based on duration is feasible whereas bandwidth is not available, then the transmission is not successful.

At Δt, two possible cases occur as follows.

Case 1: $\sigma_0 > \sigma_n$, the number of vehicles connected to the novice vehicle at time Δt is high, therefore, $b_u(\Delta t) \gg \mathrm{ld}(\Delta t)$. The additional number of rerouting procedures equals $\sigma_0 - \sigma_n$. In this case, ld ceases until $\sigma_0 < \sigma_n$ or $\sigma_0 = \sigma_n$. Therefore, the novice vehicle will undergo a handoff process.

Case 2: $\sigma_0 \le \sigma_n$, ld is a maximum, increasing the time of connectivity. Therefore, Eq. (7) is simplified to

$$\mathrm{f(np)} = \begin{cases} \max\,(\mathrm{ld}) \\ 0,\ \text{otherwise} \end{cases} \quad (9)$$

The handoff requiring time will be further extended to $\Delta t + t$ with $\sigma_0 > \sigma_n$ in t. Hence, if the neighbor density is low, then the handoff requires a protracted time period, minimizing frequent rerouting.

From the analysis of the above two cases, Case 2 is the ideal condition providing an optimal neighbor selection. Achieving an ideal condition is not always possible due to the unpredictable acceleration and direction of vehicles. Nevertheless, the above solutions are defined by considering the distance metric computed in Eq. (3). The shorter the distance between the BS and the experienced vehicle, the higher is the preference for neighbor selection of the novice vehicle. Because the other vehicles in the network were experienced, the beaten links were followed that minimized interference in communication. The process of neighbor selection is described in Algorithm 1 below.

Algorithm 1 Neighbor discovery.

Inputs: V_n, V_e, $p_n(x_n, y_n)$, $p_e(x_e, y_e)$
Neighbor Discovery Algorithm () {
Begin {
V_n requests for service from BS
$\forall$ V $\in R_v(V_n)$ do {
Compute bu using eq. (1)
Compute ld using eq. (5)
l1:
Construct a preference function f(np)
$\mathrm{f(n,\ p)} = \begin{cases} min\ (bu) \\ max(ld) \end{cases}$
if ($\sigma_o \le \sigma_n$) then
Initiate communication between V_n and BS through V_e
Update bu, ld
end if
if ($\sigma_o > \sigma_n$) then
call adaptive handoff ()
end if
}
} **end**
}
Output: Path discovery for V_n

3.3.2. Q-Learning-based adaptive neighbor selection

In the Q-learning-based neighbor selection stage, the re-routing process of the VANET is restructured so that it does not interrupt the other neighbors' communications. As opposed to novice neighbor selection in the first stage, the neighbor is now selected from among the experienced vehicles. In the presence of unreliable neighbors, re-routing due to handoff in a VANET leads to latency and packet loss. Latency of the handoff process is due to the outage time of the handoff-vehicle. A communication scenario will be analyzed where the soft handoff process ceases due to an unexpected wait time to discover a PoA.

The handoff-requesting vehicle stores the information about the other vehicles in its range. This information is 4-bytes long and contains vehicle identification, reward value, and neighbor information. The details of the neighbor from R_v are updated in the saved information. The information on the other vehicle exists in a reward updated by the BS, periodically facilitating optimal selection of neighbors. The problems of storage overflow and profitable neighbor costs based on information transmission are evaluated for the available vehicles to compute the reward. These two metrics are assessed to grant an optimal re-routing (or near-optimal to the previous best solution) for the vehicles in handoff. The profit of a neighbor depends on the reliability of the information it shared previously, and that is updated in the reward. The reliability of information sharing was derived from the previous handoff session of the vehicle that ensured maximum communication. The probability of a vehicle identifying a reliable neighbor throughs hops based on its history (q_r^s) is

$$q_r^s = \tau_r^s * \prod_{i-1}^{s-1} \left(1 - \tau_r^i\right) \tag{10}$$

where τ_r^i is the probability of the vehicle obtaining the related information. Similarly, the cost for obtaining the information located m hops away (C_m) is computed using

$$C_m = \sum_{r-1}^{r_{\max}} r * q_r^s \tag{11}$$

where $r_{\max}$ is the maximum number of reliable solutions available.

The next related metric is the storage utilization of the neighbor. To accept the active handoff request and pursue communication, the neighbor must be capable of accepting the request, which relies entirely on the neighbor's available storage. The storage utilization of the neighbor determines if it is busy or idle towards the incoming handoff request. If storage utilization is low, then the number of handoff requests serviced is high and vice versa. The storage utilization (s_{util}) of the vehicle is computed using

$$s_{\text{util}} = (1 - \partial_t) * s_s + s_{\text{util}} * \partial_t \tag{12}$$

where ∂_t is the transmission weight factor and s_s is the storage size.

The base station updates the vehicles' communication information packets after the handoff and other modes of communication. The handoff requesting neighbors obtain the most recently updated information from the BS, which then assigns rewards to the vehicles that are present within the range. The reward is estimated using the profitable cost and storage utilization. In a Q-learning process, the first step is to evaluate a reward criterion $(\mu(v))$ for acting on a decision. Action is related to the state of the vehicle, which relies on a handoff or without a handoff. The reward of a vehicle determines its state of action followed by handoff and is computed with

$$\mu(v) = \begin{cases} \max\{s_{\text{util}} \cup C_m\}, & \text{if } \sigma_0 > \sigma_n \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

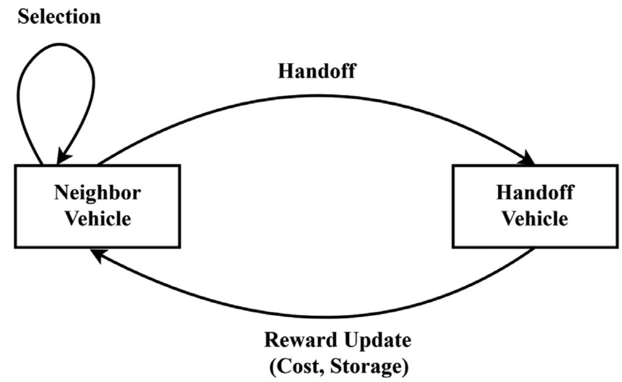

Fig. 3. The learning process.

With respect to the reward criterion, the process of the Q function is represented as

$$Q\left(R_{\mu(v)+1}, \text{HO}\right) = Q\left(R_{\mu(v)}, \text{HO}\right) + \propto \left(r_i\left(R_{\mu(v)}, \text{HO}\right) - Q\left(R_{\mu(v)}, \text{HO}\right)\right) \tag{14}$$

Here, HO represents the handoff decision, and α is the learning rate, where $\alpha \in [0, 1]$. The vehicle saves the information of the rewarded vehicle with its ID, reward value, and time of update. After the handoff, if the vehicle has a chance to interact with the same vehicle again, then it updates the current reward value with the time. The update of current reward value minimizes unreliable neighbor selection using short-lived metrics, such as distance and time delay. The newer the update, the more precise is the selection criteria. Therefore, the routing process is re-instigated through the neighbors satisfying the reward for which the decision is made. This complete process of learning is illustrated in Fig. 3.

After the handoff process, the reward of the vehicles is updated and observed for all communication over Δt to provide near-optimal knowledge of the vehicles to the HO requesting vehicles. The process of learning is imposed on the vehicles to improve communication reliability over time in both modes of communication. The observed vehicle is updated with its current reward value by the BS. The process of the learning-based adaptive neighbor selection is described in Algorithm 2 below.

Algorithm 2 The adaptive handoff.

```
Input: V_e
Adaptive handoff () {
Begin {
∀ V_e requesting HO {
Discover {V} ∈ R_v(V_e)
Compute S_util and C_m ∀ {V} using eqs. (12) & (11)
compute μ(V) using equation (13)
Define the Q function for initiating HO
while (σ_0 > σ_n) then
V_e HO to max {μ(V)}
if (σ_0 ≤ σ_n) then
call Neighbor Discovery ()
break;
end if
end while
}
} end
}
Output: HO decision
```

4. Results and discussion

The performance of the NPAH is assessed through an implementation using the Network Simulator in an urban mobility

Table 1
Simulation parameters.

Simulation parameter	Value
Traffic simulator	SUMO-0.15.0
Number of vehicles	60
MAC	802.11p
Channel model	Rayleigh Fading
Connection type	UDP
Vehicle speed	60–100 Km/h
Packet size	80 bytes
R_v	50–500 m

topology. Both V2I and V2V communication modes were modeled for 60 vehicles with varying speeds of 60–100 km/h. Table 1 shows the basis simulation settings and values. NPAH was assessed using the metrics of the delivery factor, packet loss, outage time, and storage utilization. The performance of the NPAH was compared with the existing PRHMM [25] and BHN-DMM [26] methods.

4.1. Impact of vehicle count

Vehicle density is a performance-determining factor that influences network metrics with availability and dynamicity. Vehicle density is constructive for switching paths and aiding handoff with minimum difficulty. Contrarily, vehicle mobility and congestion are the adversary factors that are to be addressed. Therefore, the importance of vehicle count is considered for the delivery factor, packet loss, and outage time.

4.1.1. Delivery factor

Fig. 4 shows the delivery factor for NPAH compared with the PRHMM and BHM-DMM methods. In the predictive handoff model, the neighbors were selected independently based on the category of communication. The communication was facilitated by evaluating the required metrics to meet the end-user application demand. The handoff occurrence was pre-estimated based on time factor $(\Delta t + t)$ and density constraints $(\sigma_0 > \sigma_n)$. The normalized and HO communications were separated to prevent interruption in either of the communication modes, which improved seamless and prolonged communication by increasing the rate of service packets flow and the successful delivery of the packets. Eq. (10) ensured the selection of reliable neighbors based on previous communications, increasing the delivery factor of the HO.

4.1.2. Packet loss

The number of interrupted communications and discontinued transmissions in the handoff scheme decreased due to individual communication modes based on the prediction. The number of isolated communications was confined to the verification of neighbor density and link duration. The preference function selected neighbors with a higher link duration before handoff (by Eq. (9)), and storage exploitation-based neighbors were preferred at the time of handoff, minimizing inconsistent transmissions. The link duration-based neighbor selection improved communication time, and storage exploitation minimized the handoff crowd, which was the vital factor affecting the communication in the VANET. As these factors were optimized, the number of packets being lost decreased considerably in NPAH as seen in Fig. 5.

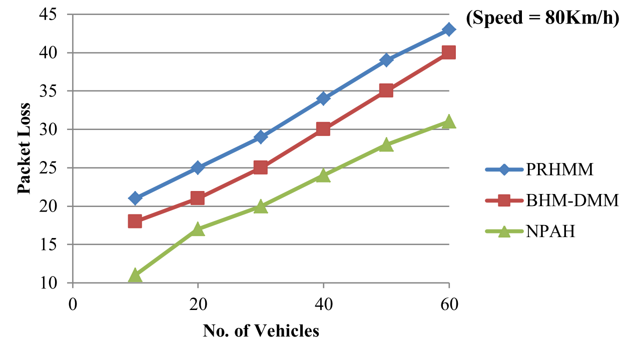

Fig. 5. Comparison of packet loss.

4.1.3. Outage time

In neighbor predictive adaptive handoff, the wait time of the handoff request decreased by estimating the $\Delta t + t$ of the novice vehicle participating in the communication. This is a predicted handoff time such that the best possible route to the available neighbor was identified using the Q-learning function. The maximum outage time observed is at the next handoff, which is greater than $\Delta t + t$. Therefore, for an available link duration, if a vehicle performs handoff, then the outage lies between Δt and $\Delta t + t$. At the point of maximum elasticity within the soft handoff, a communication link was ensured for the requesting vehicle. Therefore, the chance of the vehicle remaining in an unattended state decreased, reducing outages (see Fig. 6) as compared to the other methods. Here, considerably less outage is experienced, and those that did occur were due to the unpredictable vehicular density and fast-moving vehicles exceeding the considered speed.

4.2. Impact of number of messages

The number of messages exchanged between two or more vehicles varies before and after the handoff. Following the handoff process, the messages demand significant storage space that must be effectively available, which impacts storage utilization. Storage management has a greater impact on other network metrics such as delivery factor and packet loss.

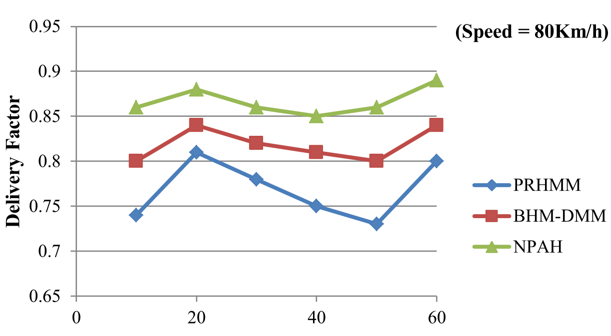

Fig. 4. Delivery factor comparisons.

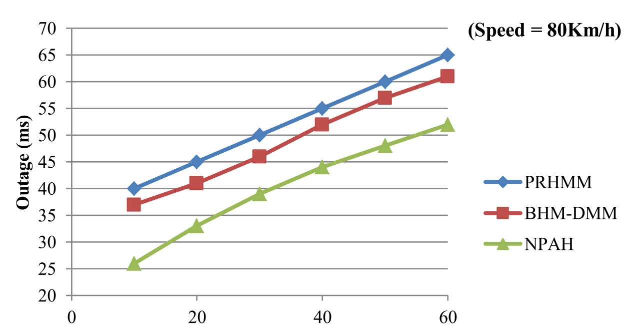

Fig. 6. Comparison of outage time.

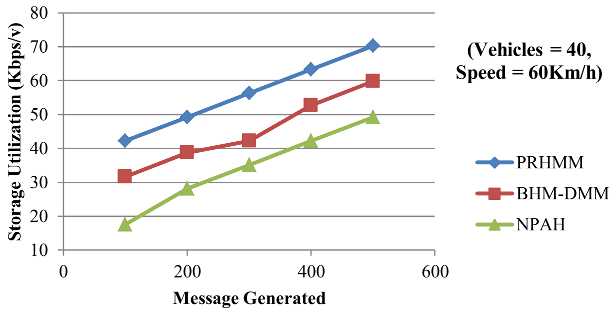

Fig. 7. Storage utilization.

Table 2
Performance comparison metric values.

Performance metric	PRHMM [16]	BHM-DMM [18]	NPAH
Delivery factor	0.8	0.84	0.89
Packet loss	43	40	31
Outage time (ms)	65	61	52
Storage utilization	70.312	59.77	49.22

4.2.1. Storage utilization

Fig. 7 shows the buffer utilization observed in the NPHA compared with the existing handoff methods. During the handoff period, the short-lived metrics were discarded, and a global update of the neighbors facilitated uninterrupted HO. The neighbor with less storage utilization was selected only when $\sigma_0 > \sigma_n$. Therefore, the overloading of a single neighbor was prevented, minimizing unnecessary storage flooding. Moreover, the constraint of the cost function ensured that a neighbor meets the storage utilization demand, curtailing the amount of active storage exploited at the time of handoff.

Table 2 lists the values of the performance metrics used for the comparative analysis.

5. Summary

Neighbor predictive adaptive handoff (NPAH) was proposed for improving mobility management in VANETs. To address challenges during handoff and transmission, the process of NPAH is divided into two independent stages of neighbor discovery and adaptive neighbor selection. Neighbor discovery is facilitated by evaluating bandwidth utilization and link availability. Adaptive neighbor is selected using Q-learning by estimating the storage utilization and cost factors. The distinct methods are integrated to select a best-fit neighbor that ensures seamless connectivity after the handoff. This learning process minimizes packet loss by confining the outage time through adaptive neighbor selection. The proposed NPAH improves the delivery factor of the network by better utilizing the storage of the neighbor. In the future, integration of caching with a non-redundant service response over a densely populated VANET will be estimated with scalability support.

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