A Lifi Approach using Dynamic Q learning in Vehicular Networks

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ABSTRACT
Vehicular Ad hoc Network (VANET) allows communication between vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications that support road safety as well as intelligent transportation systems (ITS) to avoid road hazards and share safety alerts. Even though traditional handover methods considering Wi-Fi and Light Fidelity (Li-Fi) technologies have seen significant improvement, dynamic network conditions experienced in VANETs need adaptive solutions. This paper presents a Li-Fi-based handover approach with a dynamic Q-Learning algorithm for deciding on the handover decision. The approach uses utilises reinforcement learning for vehicle traffic, vehicular mobility, network occupancy, and signal strength as parameters, thereby optimizing handover performance in high-mobility scenarios. The simulated results show that the handover mechanism outperforms other techniques over multiple criteria's such as latency, handover success rate, network throughput and performs more decisional handover.

Keywords
Li-Fi, handover decision, vehicular networks, reinforcement learning, adaptive communication.

1. INTRODUCTION
VANETs refer to the automobile part of ITS which enhances the intelligence both on vehicles and infrastructure sides to communicate with each other towards safety of roads, management of traffic flow, and real-time services like collision avoidance and optimal path. This system allows for sharing of critical safety information between the vehicles, hazardous road conditions, observations of potential collisions and information about real-time traffic information to support adequate and timely responses and informed decisions on the road. The high speed of vehicles, frequent change in network connectivity, and the varying availability of communication infrastructure make it especially difficult in VANET handover management [1]. Application requirements in VANETs are extremely demanding and need to be supported by handovers including collision warnings, emergency alerts, and notifications of road hazards. All of these require high reliability with low latency; delay or packet loss caused by handover failures or delays leads to serious degradation in quality of service (QoS) in scenarios of split-second decision making such as highway driving or negotiating busy urban centers. Highways, where vehicles travel at a high speed, and congested city centers, where traffic is usually locked up, represent environments for which efficient management of handover is critical[2].

Generally, conventional handover techniques used in VANETs are based on using signal strength thresholds and static criteria to decide when to execute a handover. They are mostly applied for stationary, low-speed environment where the network conditions do not change often. However, in high mobility environments static approaches have highly suboptimal performances [3]. These numerous handovers create overheads, and network performance degrades since several such handovers may be initiated prematurely or late, thus causing losses of packets, increased latencies, and generally poor communication quality under such safety-critical conditions[4]. Therefore, these critical challenges that exist within traditional handover management techniques call for developing adaptive and dynamic handover management techniques that may function in real-time response to alterations in network conditions.

Li-Fi is another choice which can be utilised in RF-based communication in VANETs where vertical handovers occur in heterogeneous networks. It transmits data through the visible light spectrum. The advantages of Li-Fi over traditional RF communication include more bandwidth, less interference, and more security [5]. Kalita et al.[6] in 2020 proposed handover mechanism of Li-Fi for VANETs using on vehicle Li-Fi sensors as well as Anonymous Announcement System (AAS) on RSUs to enable Li-Fi VANET handover in an active manner. They found that in comparison to systems based upon the RF techniques, their system outperforms especially in terms of latency as well as the Packet data rate (PDR). Li-Fi-based systems relies upon line of sight (LOS) communication, it might face coverage gaps, particularly in the urban environment where obstacles are very likely. Therefore, integration of Li-Fi with adaptive decision-making algorithms like reinforcement learning is essential for taking full advantage of its capabilities in VANETs[7].

This paper intends to bring out an efficient ML based handover mechanism to overcome the challenges due to the dynamic nature of VANETS and at the same time utilise Li-Fi technology to enhance overall performance of communication systems based on VANETs. This paper is organised as follows. Chapter 2 presents the related work. Chapter 3 provides description on the methodology, followed by the results and discussions in Chapter 4. Finally the conclusion with future work is addressed in Chapter 5.

2. RELATED WORKS
Some of the recent studies have presented numerous handover mechanisms to support VANETs. Duo et al. introduced an SDN-based approach for hybrid networks in [8] but had scalability issues. Dwivedi et al. [9] proposed the B-HAS protocol for safe handover but had very high computational overhead. Aboud et al. [10] tried to minimize delays in 5G VANETs but had difficulties in heterogeneous cases. Xie et al. [11] and Son et al. [12] suggested blockchain-based lightweight protocols with scalability issues. Alam et al. [13] presented reviews on handover techniques without the practical implementation. Rosli et al.[14] presented the issue of handovers in 5G with energy costs. Costa et al. [15] optimized video distribution in a handover process without touching security aspects. Oladosu et al. [16] provided a metaheuristic algorithm and neglected adaptability. Also the works of Anilkumar and Rafeek [17] have put forward the "Soteria" certificate less mechanism that could be subject to latency issues due to implementation of blockchain with changing

scenarios.

Late developments of intelligent handover management systems, especially implementing machine learning approaches, have recently shown promising approaches toward filling these deficiencies. One such promising approach is the application of the model-free reinforcement learning (RL) technique called Q-Learning in optimizing handover decisions within VANETs. Q-Learning enables real-time learning and adaptation of parameters such as the velocity of a vehicle, network traffic, and signal strength by the system in an attempt to adapt the decision-making process. Q-Learning-based systems constantly evolve their policies deciding their future actions based on the changing network state, so more efficient and adaptive ways of handover management could be achieved [18].Overall, this leads to a reduction of the handover frequency, while optimum performance of the system is preserved in terms of latency, throughput, and QoS[19]. The authors of [20] provided the first Q-Learning application to VANET where decisions on handover are made according to network conditions based on real time evaluation. Proving their work, the authors demonstrated that the system based on RL techniques can work better than threshold-based handover schemes under network fluctuations .Subsequent studies, such as those carried out by Mohammadi et al.[21], make Q-Learning for handover management more feasible with additional parameters such as vehicle density, traffic load, and signal quality added to it.

Liang et al. [22] developed an extensive comparison between traditional threshold-based handover methods with Q-Learning-based systems in VANETs. According to their results, machine learning-based handover mechanisms reduce latency by significant amounts and boost packet delivery ratios since they adapt to real-time network conditions dynamically Hao Wang and Bo Li [23] proposed a double-deep Q-learning-based handover management system for mmWave heterogeneous networks with dual connectivity in order to enhance the efficiency of handovers and minimize latency in high-mobility scenarios. The approach could be computationally intensive as the scale of the network increases. Jiao He et al. [24] proposed a reinforcement learning-based handover parameter adaptation method using LSTM-aided digital twins for ultra-dense networks, which improves the accuracy of predictions and adaptability in dynamic environments. However, this method depends on the vast amount of data for training, and its applicability in real-time is still limited to fast-changing scenarios. Therefore, a hybrid technology might be necessary combining Li-Fi with RF-based communication systems in order to achieve seamless connectivity from environment to environment. Unlike static handover methods, which depend on predefined thresholds, the integration of Q-Learning into the handover actually enhances the system's adaptability with respect to changes in network conditions, but it also opens the possibility of taking better advantages of network resources.

Extensive research has been done on VANET handover management, with different technologies such as Wi-Fi, blockchain, and 5G. However, a lot of gaps still remain in the following aspects:

- Adaptive Solutions: All blockchain and metaheuristic methods focus on static handover decisions, not adaptive to dynamic vehicular conditions such as changing traffic patterns and mobility.
- Limited Li-Fi Integration: Handover mechanisms of emerging Li-Fi technology are under-explored. Largely, not many researches apply reinforcement learning or Q-learning in the real-time, adaptive optimization of handover for handling the change in traffic density, strength of signals, or even congestion.
- Performance Overlooked: Research focuses more on security (e.g., blockchain solutions) than on performance metrics such as latency, success rates, and throughput, especially in high-mobility scenarios.

This paper addresses the gap by proposing an adaptive Li-Fi handover technique that relies on a dynamic Q-Learning algorithm. Inclusion of vehicular mobility, traffic patterns, network occupancy, and signal strength in its decision-making procedure will assist in significantly optimizing the performance of the handover in VANET, thereby having reduced latency, higher success rates in handover, and improved overall network throughput. This is a new contribution to the domain of communication, especially in high-mobility scenarios where the traditional static methods are likely to fail.

3. METHODOLOGY

The handover management system based on the basic work[6] proposed for Li-Fi-based handover techniques is being implemented with the use of Q-Learning algorithm for handling handover decisions in real-time. The system is designed to operate in a VANET environment using fixed wireless access (FWA) technology. These vehicles are equipped with on-board units consisting of their core wireless transceivers, sensors, and GPS systems. These will thus be able to communicate with the base stations. The bases have been mounted with Active Antenna Systems and multiple input multiple output (MIMO) technology so that they can work efficiently with the vehicles both by Li-Fi and Wi-Fi.

The proposed system relies on a dynamic Q-learning system that perpetually considers network occupancy (NO), vehicular mobility(VMo), and signal strength (SS). Based on these parameters in a real-time situation, the algorithm switches dynamically to the most appropriate communication medium. The vehicle platform maintains the two interfaces on-board (Li-Fi and RF-based), which allows fast vertical handoffs without packet losses. Another advantage of AAS at the RSUs is that it ensures seamless connectivity across heterogeneous links, thus reducing handover delays and interruptions. The considered parameters are discussed in detail in below sections.

3.1 Signal strength (SS)

The signal coverage area (SCA) is represented in this work by a circular region. Therefore the SS is defined on the distance (di) between the 2 base stations which is given as:

$$di = 4\int_{d/2}^{x} \sqrt{r^2 + x^2}\, dx \quad (1)$$

$$SS = k.1/di \quad (2)$$

Where, k = no of network phases

$$(ss)=[-\log(P(ss))] \quad (3)$$

The Shannon entropy [25] for signal strength is defined as S(ss), while P(ss) denotes the probability of the signal strength

3.2 Network occupancy (NO)

The network occupancy is monitored by using Traffic Load (TL).The traffic load is dependent on two factors; vehicle traffic (VT) in the network defined by the average queue size ($qavg$) and number of vehicles (m). The value of m is defined for the vehicles in its 1-hop distance.

$$TL = qavg * m \quad (4)$$

For calculating the $qavg$, we apply little's theorem [26] as follows, the average number of vehicles in a SCA (Np) is dependent on the arrival rate of vehicles into the SCA (λ) and the average amount of time a vehicle spends in the SCA(T) given by

$$Np = \lambda.T \qquad (5)$$

If the leaving rate of vehicles from the SCA can be denoted by μ, Np and T can be formulated as:

$$Np = \frac{\lambda}{\mu-\lambda} \qquad (6)$$

$$T = \frac{1}{\mu-\lambda} \qquad (7)$$

If we consider T to include the queuing delay plus the service time Ts, the total time spent in the queue (Tt) can be calculated as

$$Ts = 1/\mu \qquad (8)$$

$$Tt = T-1/\mu \qquad (9)$$

The $qavg$ can be obtained from (5), (7) and (9)as

$$qavg = \lambda Tt$$

$$= \frac{\lambda}{\mu-\lambda} - \frac{\lambda}{\mu}$$

$$= Np - \beta \qquad (10)$$

Here,β is the optimal traffic transfer ratio.

3.3 Vehicular mobility (VMo)

The Vehicular mobility (VMo) of each node represents the movement of vehicles, and how it changes overtime. In order to measure suchVMo, the difference between average speed (Avs) of the nodes in final and initial location is estimated in $'t'$ time units. Dist is the distance between 1 hop vehicles. This can be presented as follows:

$$Avs = \frac{Dist}{t} \qquad (11)$$

$$VMo = Avs\ (final) - Avs\ (initial) \qquad (12)$$

The Active network lifetime (ANL) can be obtained by the minimum value of the weight (Wt) associated with the vehicles in a SCA. This weight (Wt) parameter is represented by the following.

$$Wt=w1.ss+w2.TL+w3.VMo \qquad (13)$$

In Eq(13), $w1$, $w2$, $w3$are represented as weight factors and the sum of these weight factors value is equal to 1 i.e., $w1+w2+w3=1$.

3.4. Q-Learning Framework

The parameters, NO and SS are the states that are taken in account to take an action for handover. Let (S,) represent state S and action A based on the Q values. Each state$S$ will have four parameters and this (S, A) is determined and updated in the rule.

$$Q(S,A)+\alpha(R+\gamma Q(S',A')-Q(S,A))\rightarrow Q(S,A) \qquad (14)$$

The term(S',A') defines next state and action R is the reward given by the agent, γ is the discount factor that is $[0-1]$, then α is the learning rate $[0-1]$ i.e.it denotes the step length to estimate the (S, A). The action is taken using ϵ −greedy policy, the ϵ represents epsilon. In ϵ −greedy policy, when the probability is ($1-\epsilon$),then the action will be taken as per the value in the Q-table. If the handover request is agreed and the action is yes, then it will select a network

3.5 Algorithm

Input–States (S),– $table$

Output–Action(A)

Begin

1. Vehicle(V1), requesting for handover

2. InitializeQ-table(S,A)

3. For each $S\rightarrow$TL, VMo,SS

3.1 Compute Active network life time threshold (Th_ANL) using equation13

3.2 If(ANL<Th_ANL)

for(eachstep)

-Apply ϵ −greedy policy obtain

-Q-value from Q-table perform action $A \rightarrow V1$

-Compute R and next state S'

3.3 update Q-table

4. update$S'\rightarrow S$

end

4. RESULTS AND DISCUSSION

This chapter presents a comparative study on the performance parameters of the proposed Q-Learning-based handover technique with the DTe-DQN[24] approach for handling handovers in VANETs. The performance is studied based on four key parameters: handover success probability, handover failure rate, ping pong rate, and overall network throughput. The experiments were performed in a simulation-based environment that entertains varying speeds and densities of VANET traffic through OMNet++ and the simulation parameters are set forth in a way as to closely mimic real vehicular mobility patterns and communication conditions. The simulation parameters used for the proposed work is summarized in Table 1:

Table 1 : Simulation parameters

Parameter	Value
Number of Vehicles	100
Maximum Speed	120 km/h
Communication Types	DSRC, LTE
Simulation Duration	300 seconds
Fading Levels	Low, Moderate, High

4.1 Probability of Handover Success

The probability of successful handover is defined as the ratio of successful handovers to the total number of attempted handovers. Fig 1 summarizes the results, which show that the Q-Learning-based approach actually resulted in a handover success probability more than 90% for high traffic scenarios. However, under similar conditions, DTe-DQN has a reported maximum success rate of 83.1%. The result of improving this system due to the adoption of an adaptive learning mechanism based on Q-Learning, which is specifically tailored to make adaptations of handovers based on real-time network conditions.

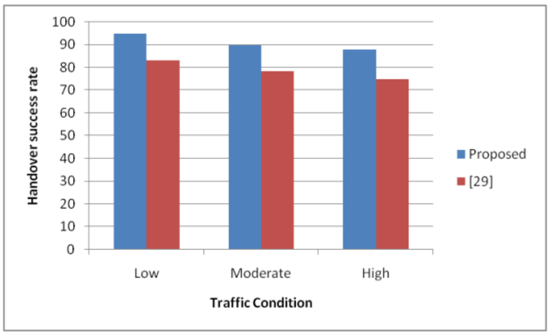

Fig 1: Handover success rate

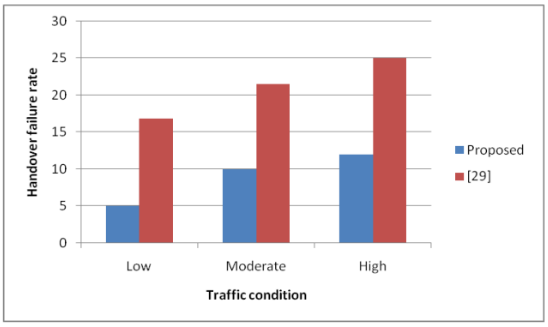

Fig 2: Handover failure rate

4.2 Handover Failure Rate

The failure rate of handover refers to the number of handovers which are failing per total number of handovers made in establishing a connection. The proposed method always keeps the failure rate lower than 10%. As shown in Figure 2, it has around a 16% failure rate with DTe-DQN. The reason for this decrease in failure rate is because of Q-Learning enabled continuous learning process, which can account for timely adjustment of handover strategies according to time-varying vehicular conditions.

4.3 Ping Pong Rate

The ping pong handovers occur when the vehicle rapidly switches between two base stations, and hence the network resources utilized is not fully efficient. The Q-Learning method attains a ping pong rate of less than 5% as presented in Figure 3. This is far below the 8-9% that is attained by the DTe-DQN method. Such a reduction therefore determines the efficiency of improving network performance since it minimizes unnecessary signaling overhead and enhances the user experience at the occurrence of events during handover.

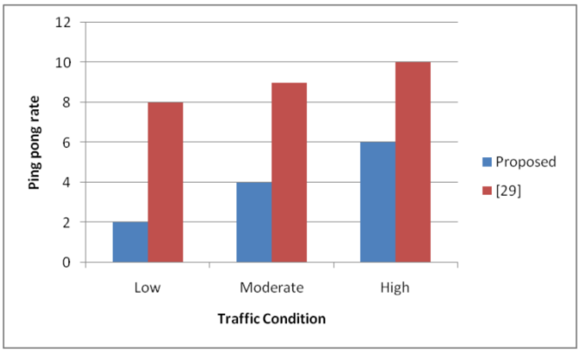

Fig 3: Ping pong rate

4.4 Throughput and Delay

Throughput and delay are two important performance metrics of the network. The proposed method succeeded in making an average improvement in throughput by approximately 20% compared to traditional methods, as can be seen from Fig 4. From Fig 5, it can be seen that the average delay on handovers decreases by about 30%. In other words, the transition time between base stations was relatively shorter. The DTe-DQN method, despite being competitive, had higher delays due to its more conservative approach toward handover, especially at higher motilities.

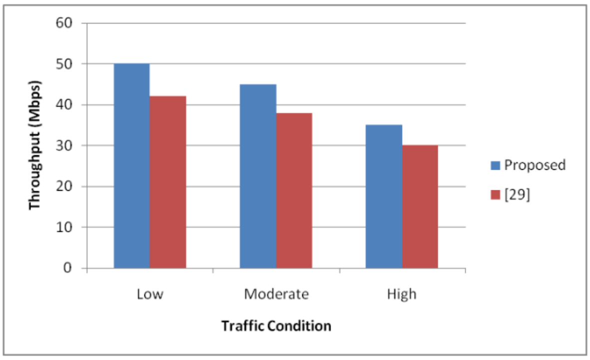

Fig 4: Throughput (mbps)

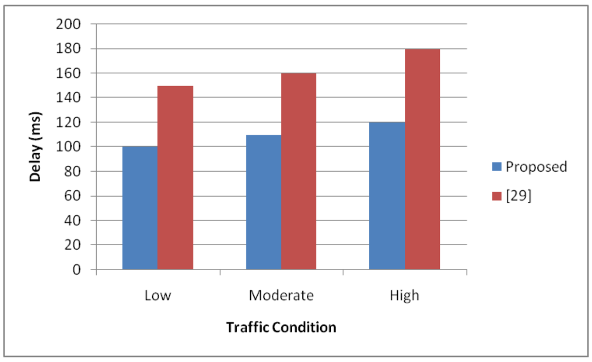

Fig 5: Delay (ms)

The results of the experimental evaluation of the proposed Q-Learning-based handover management strategy clearly indicate that, in comparison to the existing ones, particularly DTe-DQN, there are considerable improvements in those approaches. The analysis shows that the Q-Learning framework performs well in different traffic conditions and hence results in higher handover success rates but lower failure rates. The Q-Learning-based method offered a handover success rate of 90% under moderate traffic conditions as compared with the 83.1% achieved using the DTe-DQN method. This may be attributed to the fact that, based on higher mobility environments, the algorithm learned and updated in real-time settings for vehicle speed and signal strength, which are parameters significant in network settings. Therefore, dynamic adjustments of handover thresholds with changed conditions will allow for timelier and better-informed handover decisions.

As it would seem, throughput improvements are also noteworthy in the proposed approach since average a throughput of 50 Mbps is achievable in low-traffic scenarios, while the DTe-DQN method reported its maximum throughput of 42 Mbps. For real-time applications such as video streams and navigation, this increase in throughput can really mean the difference for end users, in terms of the quality of network performance, which impacts user experience.Quality enhancement of the model is, therefore, provided by being highly scalable for any resolved decision making in the presence of an increasing number of vehicles (up to 100 in the current simulation). Maintaining handovers with higher success ratio with minimal degradation of important performance related metrics such as latency and ping pong rates. Since Q-learning adjusts beforehand on transitions from one state to another, this type of learning has a robust scalability property. Therefore, the results strongly promote the strategy of Q-Learning-based reinforcement learning to allows it continuously learn and optimize itself, and therefore might be a good solution for the problems with handover implementation in VANET.

5. CONCLUSION

The proposed dynamic Q-Learning-based handover management strategy significantly outperforms the current state of art and methods, even including the DTe-DQN approach, in terms of success rates, failure rates, ping pong rates, throughput, and delay. The experiment results imply that the proposed approach is capable of adaptive response to the changing environment conditions normally prevailing in vehicular environments for seamless communication and improved network performance. It is also compatible with existing VANET architectures as it operates at the network layer and can be deployed as an overlay module on top of current communication protocols such as DSRC, LTE, or even 5G-based VANETs. Future work will be focused in developing the Q-learning algorithm, further improving it with the implementation of extra context-aware parameters, like environmental conditions and vehicle behaviour and study of deep reinforcement learning techniques.

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