Dynamic Q-Learning-Based Handover in VANETs: An Approach for Li-Fi Based Handover Techniques

Chinmoy Sailendra Kalita Maushumi Barooah

*Assam Engineering College, Assam Engineering College,*

*Guwahati, Assam, India Guwahati, Assam, India*

**Abstract. Vehicular Adhoc 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 hand over 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, Q learning, latency**.

# 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 hand overs 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 utilized inRF- 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 and Barooah[6]proposed a 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 interms 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 utilize Li-Fi technology to enhance the overall performance of communication systems based on VANETs. This paper is organized as follows. Chapter 2 presents the literature review. Chapter3providesdescriptionon the methodology, followed by the results and discussions in Chapter 4. Finally the conclusion with future work is addressed in Chapter 5.

# Literature review

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]haveput 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 hand over 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 statichandover 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 oftaking 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, suchas changing traffic patterns,mobility. adaptive optimization of handover for handling the changein traffic density, strength of signals,

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.

# 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. Three parameters have been considered in designing the Q learning handover system which are: Vehicular mobility(𝑉𝑀𝑜),network

occupancy(NO)and signal strength(SS), which are explained as follows:

* 1. **3.1 Signalstrength(SS)**

The signal coverage area (SCA) is represented in our 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∫\_(d/2)^x√(r^2+x^2)dx (1)

SS=k.1/di (2)

Where, k =no of network phases (𝑠𝑠)=[−log(𝑃(𝑠𝑠))] (3)

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

* 1. **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 (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=λ.T (5)

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

Np=λ/(μ-λ) (6)

T=1/(μ-λ) (7)

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

𝑇𝑠=1/μ (8)

𝑇𝑡=T-1/μ (9)

The𝑞𝑎𝑣g can be obtained from(5),(7)and(9)as

𝑞𝑎𝑣g=λ𝑇𝑡

=λ/(μ-λ)-λ/μ

=Np–β (10)

Here, β is the optimal traffic transfer ratio.

* 1. **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=Dist/t (11)

VMo=𝐴(final)–𝐴𝑣𝑠(initial) (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 (13)

In Eq(13), 𝑤1, 𝑤2, 𝑤3are represented as weight factors and the sum of these weight factors value is equal to 1 i.e., 𝑤1+𝑤2+𝑤3= 1.

* 1. 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 state𝑆 will have four parameters and this(𝑆,𝐴)is determined and updated in the rule.

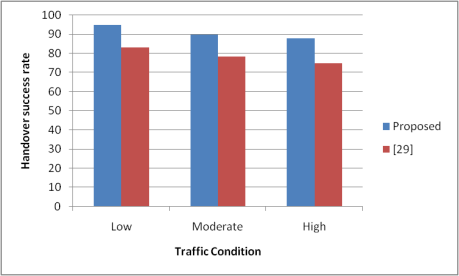
𝑄(𝑆,𝐴)+𝛼(𝑅+𝛾𝑄(𝑆′,𝐴′)−𝑄(𝑆,𝐴))→𝑄(𝑆,𝐴) (14)

The term(𝑆′,𝐴′) in Eq.(14) 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−𝜖),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

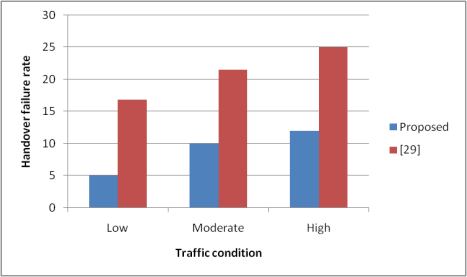
# Results and Discussions

This chapter presents a comparative study on the performance parameters of our 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 an OMNeT++ simulated environment.

The probability of successful handover is definedas the ratio of successful handovers to the total number of attempted handovers. Figure 2 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.



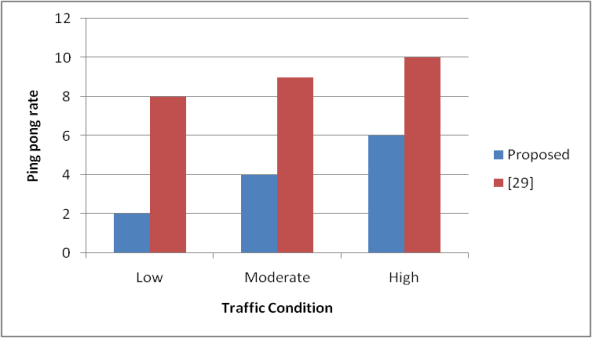
**Fig1**:Handover success rate



**Fig2:**Handover failure rate

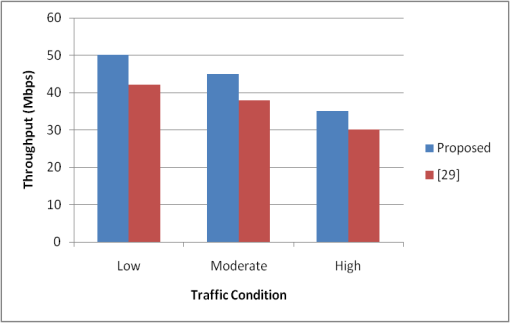
The proposed method always keeps the failure rate lower than 10%. As shown in Figure 3, it has around a 16% failure rate with DTe-DQN. The reason for this decrease in failure rate is because of Q-Learning enabled continuous learning process, which can account for timely adjustment of handover strategies according to time-varying vehicular conditions. The Q-Learning method attains a ping-pong rate of less than 5% as presented in Figure 3 below. This is far below the8-9% 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.



**Fig3:**Ping pong rate

The proposed method succeeded in making an average improvement in throughput by approximately 20% compared to traditional methods, as can be seen from Figure 4.



**Fig4**:Throughput(Mbps)

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.

# 7. 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. 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.

References

1. Saini, M., & Mann, S., “Handoff schemes for vehicular ad-hoc networks: A survey,”International Journal of Innovations in Engineering and Technology, pp. 86-91, (2010).
2. Zeadally, S., Hunt, R., Chen, Y., Irwin, A., & Hassan, A., “Vehicular ad hoc networks (VANETs): status, results, and challenges,” Telecommunication Systems, vol. 50, no. 4, pp. 217-241, (2012).
3. Pack, S., & Choi, Y., “Fast handoff scheme based on mobility prediction in public wireless LAN systems,” IEE Proceedings-Communications, vol. 151, no. 5, pp. 489-495, (2004).
4. Chang, Y.-T., Ding, J.-W., Ke, C.-H., & Chen, I.-Y., “A survey of handoff schemes for vehicular ad-hoc networks,” in Proceedings of the 6th International Wireless Communications and Mobile Computing Conference, pp. 1228-1231,(2010).
5. Wang,Y.,&Haas, H., “Dynamicload balancing with handover in hybrid Li-Fi and Wi-F in networks,” Journal of Lightwave Technology, vol. 33, no. 22, pp. 4671-4682, (2015).
6. Kalita, C. S., &Barooah, M., “Li-Fi based handoff technique in VANET,” in 2020 International Conference on Computational Performance Evaluation (ComPE), (2020).
7. Zhang, Z., Boukerche, A., Pazzi, R., &Kalfane, M., “A novel multi-hop clustering scheme for vehicular ad-hoc networks,” in Proceedings of the 12th ACM International Symposium on Mobility Management and Wireless Access, pp. 35- 42,(2013).
8. Duo, R., Wu, C., Yoshinaga, T., Zhang, J., &Ji, Y., “SDN-based handover scheme in cellular/IEEE 802.11p hybrid vehicular networks,” Sensors (Basel, Switzerland), vol. 20, (2020).
9. Dwivedi, S., Amin, R., Vollala, S., & Khan, M., “B-HAS: Blockchain-Assisted Efficient Handover Authentication and Secure Communication Protocol in VANETs,”IEEE Transactions on

NetworkScienceandEngineering,vol.10,pp. 3491-3504, (2023).

1. Aboud, A., Touati, H., &Hnich, B., “Handover Optimization for VANET in 5G Networks,” 2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC), pp. 1-2, (2021).
2. Xie, Q., Ding, Z., Tang, W., He, D., & Tan, X., “Provable Secure and Lightweight Blockchain- Based V2I Handover Authentication and V2V Broadcast Protocol for VANETs,” IEEE Transactions on Vehicular Technology, vol. 72, pp. 15200-15212, (2023).
3. Son, S., Lee, J., Park, Y., Park, Y., & Das, A., “Design of Blockchain-Based Lightweight V2I Handover Authentication Protocol for VANET,” IEEE Transactions on Network Science and Engineering, vol. 9, pp. 1346-1358, (2022).
4. Alam, S., Sulistyo, S., Mustika, I., & Adrian, R., “Review of Potential Methods for Handover Decision in V2V VANET,” International Conference on Computer Science, Information Technology, and Electrical Engineering (ICOMITEE), pp. 237-243,(2019).
5. Rosli, M., Razak, S., &Yogarayan, S., “5G handover issues and techniques for vehicular communications,” Indonesian Journal of Electrical Engineering and Computer Science, vol. 23, pp. 1- 10, (2023).
6. Costa, A., Pacheco, L., Rosário, D., Villas, L., Loureiro, A., Sargento, S., &Cerqueira, E., “Skipping-based handover algorithm for video distribution over ultra-dense VANET,” Computers Networks, vol. 176, p. 107252, (2020).
7. Oladosu, G., Tu, C., Owolawi, P., &Mathonsi, T., “Intelligent Metaheuristic-based Handover Algorithm for Vehicular Ad hoc Networks,”Journal of Communications, vol. 18, pp. 589-598, (2023).
8. Anilkumar, S., &Rafeek, J., “Soteria: A Blockchain Assisted Lightweight and Efficient

|  |  |  |
| --- | --- | --- |
| Certificate less | Handover | Authentication |
| Mechanism for | VANET,” | 3rd International |
| Conference on | Advances | in Computing, |

Communication, Embedded and Secure Systems (ACCESS), pp. 226-232, (2023).

1. Liang, W., Li, Z., Zhang, H., Wang, S., &Bie, R., “Vehicular ad hoc networks: architectures, research issues, methodologies, challenges, and trends,” International Journal of Distributed Sensor Networks, vol. 11, no. 8, p. 745303, (2015).
2. Zhang,Z.,Boukerche,A.,&Pazzi,R.,“Anovel multi-hop clustering scheme for vehicular ad-hoc networks,” in Proceedings of the 9th ACM International Symposium on Mobility Management and Wireless Access, pp. 19-26,(2011).
3. Kafle, V. P., Kamioka, E., & Yamada, S., “CoMoRoHo: Cooperative mobile router-based handover scheme for long-vehicular multihomed networks,” IEICE Transactions on Communications,vol.89,no.10,pp.2774-2785,

(2006).

1. Mohammadi, M., Shiri, H., &Ghaznavi, M., “Optimized handover management in VANETs using Q-Learning,” IEEE Access, vol. 8, pp. 123456-123471, (2020).
2. Liang, W., Zhang, H., &Bie, R., “Vehicular ad hoc networks: A literature survey,” Journal of Network and Computer Applications, vol. 43, pp. 357-373, 2014.
3. Wang,H.,&Li,Bo.,“Double-deepQ-learning- based handover management in mm Wave heterogeneous networks with dual connectivity,” Transactions on Emerging Telecommunications Technologies, vol. 35,( 2023).
4. He, J., Xiang, T., Wang, Y., Ruan, H., & Zhang, X., “A Reinforcement Learning Handover Parameter Adaptation Method Based on LSTM- Aided Digital Twin for UDN,” Sensors, vol. 23, p. 2191, (2023).
5. Cincotta, P., Giordano, C., Silva, R., &Beaugé, C.,“The Shannon entropy: An efficient indicator of dynamical stability,” Physica D: Nonlinear Phenomena, p. 132816, 2020.
6. Little’s Result, SpringerLink, 1041, https://doi.org/10.1007/978-0-387-09766-4\_2192, (2011).