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NLADSS: Design of Connectivity as a Service (CaaS) Model using Node-Level Augmentation & Dynamic Sleep Scheduling for Heterogeneous Wireless Network Handoffs

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Abstract: Seamless connectivity is need-of-the-hour for high-speed wireless networks. With the advent of 5th Generation (5G) wireless devices, users from different networks require inter-network connectivity with minimum packet drops, and maximum bit-rate. In order to perform this task, high efficiency handover models are proposed, which evaluate various network-level parameters including trust-levels, capacity, Quality of Service (QoS), etc. These algorithms also evaluate various node level metrics which include end-to-end delay, Received Signal Strength Indicator (RSSI), movement patterns, etc. in order to map the nodes to relevant networks. The drawback of proposed approaches is their inability to cater high-speed environments without causing QoS degradation. Moreover, most of these models do not consider node-level augmentations, which restricts their performance when applied to real-world scenarios. In order to remove these drawbacks and make the algorithms perform well with high speed environments without QoS degradation, we propose the design of a novel Connectivity as a Service (CaaS) model that uses Node-Level Augmentation & Dynamic Sleep Scheduling (NLADSS) for high efficiency heterogeneous wireless network handoffs. It was observed that the proposed algorithm is able to achieve a handoff efficiency of 98% for 5G heterogeneous networks, which outperforms most of the recently proposed models. The proposed model also aims at providing immutability, traceability, and high-performance distributed computing, while not compromising on QoS performance of the network.

Keywords: Heterogeneous, Sleep-scheduling, Machine learning, QoS, Q-learning.

Nomenclature

To help readers' understanding, a notation list is added in Table 1, to define the variables in equations.

1. Introduction

The design of handover mechanisms for wireless networks is a multidomain task, which involves estimation of node & network level parameters, their correlative analysis, feedback learning, make-before-break operations, etc. During handover, the network controller (or base station) evaluates a wide array of parameters, including node score, current network score, and target network score. The node score is evaluated using Eq. (1) as follows,

$$S_{node} = F_{node}(N_e, N_d, N_p, N_{rssi}, N_{oth}) \quad (1)$$

Where, $S_{node}, N_e, N_d, N_p, N_{rssi}, and\ N_{oth}$ represents node score, residual energy, communication delay, received signal strength, and other parameters respectively, while $\mathrm{F}_{\mathrm{node}}$ represents the node function which combines these parameters for obtaining the score value. Similarly, the current & target network score is evaluated using Eq. (2),

$$S_{net} = F_{net}(NW_c, NW_b, NW_d, NW_{oth}) \quad (2)$$

Where, $S_{net}, NW_c, NW_b, NW_d, and\ NW_{oth}$ represents network score, network capacity, bandwidth, data rate, and other parameters as

Table 1. The list of symbols and notations used in this paper

S_{node}, N_e, N_d, N_p, N_{rssi}, N_{oth}	node score, residual energy, communication delay, received signal strength, and other parameters.
S_{net}, NW_c, NW_b, NW_d, NW_{oth}	network score, network capacity, bandwidth, data rate, and other parameters
x, y, NB_x, NB_y	location of node, and its nearest base station
Q_{new}, Q_{old}, R	new Q value, old Q value, and reward value
RSSI	Received Signal Strength Indicator
T_w, T_{TC}, $N_{R_{sel_j}}$	node's wake up time, total cycle time, node selected using Q-Learning
N_{speed}, $N_{velocity}$, N_{RSSI}, N_{BW}, max(f)	Speed, Velocity, RSSI, Bandwidth for given node I and max values used in order to normalize the parameters.
$d(N_{r_2}B)$, E, J, PDR, N_C	distance between selected node and base-station, residual energy, jitter, and temporal packet delivery ratio of randomly selected node over N_C communications
R, $N_{R_{random}}$, $N_{R_{node}}$	Reward value, Rank of the randomly selected node, and rank of the communicating node

decided by the algorithm, while F_{net} indicates network function, which combines all network parameters to form a score value. Based on these scores, a node-to-network mapping model is developed. This model utilizes temporal score values in order to handoff nodes from current network to target network.

A survey of such models along with their nuances, advantages & limitations can be observed from section 2 of this paper. Most of these models work by contemplating node & network internals for reducing handoff latency, and improving network QoS. But these models do not utilize peer-to-peer communications & sleep scheduling capabilities for further improving handoff performance without compromising on network security. Based on this observation, section 3 describes design of Connectivity as a Service (CaaS) model using Node-Level Augmentation & Dynamic Sleep Scheduling (NLADSS) for heterogenous wireless network handoffs. The model also utilizes machine learning sidechains for improving attack resilience without effecting QoS performance during handoff. This model also initially performs node-level clustering, which divides them into high, medium & low-capacity nodes. This division assists in performing intra-cluster analysis for improved handover performance.

Furthermore, in order to improve QoS performance, the model utilizes dynamic sleep scheduling for nodes. Due to which, low-capacity nodes are able to conserve their resources, and utilize neighbouring high-capacity nodes for control-signal transmissions. Sleep cycles of these nodes are controlled using an incremental Q-learning approach, which assists in reducing scheduling delay, and improving handoff performance. Performance evaluation of the NLADSS model was done on a wide variety of simulation environments, and it was observed that the proposed model is 8% more efficient in terms of handoff efficiency, 6% more effective in terms of QoS performance, and 14% more efficient in terms of connectivity performance when compared with recently proposed models.

The proposed model was tested on different network configurations, and its performance can be observed from section 4 of this paper. This performance was compared with various state-of-the-art models, and it is observed that the proposed model outperforms them with respect to both QoS and handoff efficiency parameters. Finally, this paper concludes with some interesting observations about the proposed model, and recommends various enhancements to further improve its scalability & performance.

2. Literature review

Due to advancements in wireless communications, design of effective mechanisms for network handoffs is of utmost importance. The work in [1-3] propose design of such models wherein Named-Data-Network (NDN), QoS-aware resource provisioning, and soft logical handover are described. These models allow network nodes to seamlessly move between different networks, with minimal effect of QoS. Due to improper authentication & access control protocols, the security of networks that use these methods is low, due to which they can be attacked by internal & external adversaries. These networks also suffer from increased delay due to complex handover process, which can be reduced using the work in [4, 5], wherein Distributed Mobility Management (DMM), and game theoretical approaches are proposed.

These approaches assist in improving handoff efficiency, without compromising on QoS performance due to their low complexity. These approaches are further extended in [6] wherein cooperative game theory is proposed. This strategy can be applied to application specific networks, and is not scalable. Scalability of this model must be improved using the work in [7], wherein cognitive radio based adaptive spectrum handoff strategy are defined. This strategy can be applied to a wide variety of network scenarios.

Models that utilize fuzzy & Kalman filtering [8], multi-objective model-based handoff [9], trust & privacy-based handoff [10], and femtocell handovers in dense 5th Generation (5G) heterogenous networks [11] are also proposed by researchers.

These algorithms are further extended by the work in [12-14], wherein security-based models, fuzzy analytic hierarchy process, and secure handoff for mobile-based cloud deployments is proposed. These models assist in improving security during handoffs, thereby reducing attack probability, and increasing overall QoS of the heterogeneous network. Similar models like, Network Mobility (NEMO) based cryptosystem [15], cooperative road topology-based handoff [16], and multiple vertical handoff decision controllers [17] are proposed by researchers. These models have good simulation performance, but do not cover majority aspects of real time communications including transition delays, security overheads, etc. due to which their applicability to network deployments is limited.

A multi-hop cluster-based architecture is proposed in [18], wherein high security & low overhead handoffs are observed. This model has better QoS performance, and is secure against a wide variety of attacks. Similar models are proposed in [19-21], wherein Trustworthy VANET ROuting with grouP autHentication keYs (TROPHY), ad hoc TROPHY (TAD-HOC), dynamic edge backup-node based handoff, and Light Fidelity (LiFi) schemes are defined. These schemes assist in improving handoff efficiency by reducing network overheads, and incorporating attack resilience models to the deployment. Based on this review it is observed that cryptographic systems, along with clustering models have better handoff performance than their counterparts inspired by this observation, the next section proposes design of Connectivity as a Service (CaaS) model with Node-Level Augmentation & Dynamic Sleep Scheduling (NLADSS) for heterogeneous wireless network handoffs. The proposed algorithm is able to achieve a good handoff efficiency for 5G heterogeneous networks, which outperforms most of the above recently proposed models. The proposed model also aims at providing immutability, traceability, and high-performance distributed computing, while not compromising on QoS performance of the network.

3. Node-level augmentation & dynamic sleep scheduling (NLADSS) for heterogenous wireless network handoffs

Mobile Wireless Networks (MWNs) consist of nodes with varying movement patterns. These patterns must be analysed for effective movement prediction, which would assist in seamless handoff. Due to variation in node-to-node communication interfaces, heterogeneous MWNs have higher level of complexity than their homogenous counterparts. This complexity varies in terms of evaluation of node metrics, evaluation of node-to-node link levels, network variations, etc. This adds to the complexity of handoff decision making, which reduces network performance, and impacts communication QoS. To address this issue, the underlying Node-Level Augmentation & Dynamic Sleep Scheduling (NLADSS) model is proposed.

The model investigates use of node heterogeneity as a parameter for clustering, and utilizes these clusters for node-to-base-station communications. Nodes belonging to high-capacity clusters assist nearby nodes belonging to lower capacity clusters, thereby improving final handoff decisions. In order to describe the proposed model, this section is divided into 4 sub-parts, wherein initially a capacity-based clustering model is described, followed by Dynamic Sleep Scheduling (DSS). The model uses incremental Q-learning in order to reduce handover delay, and improve QoS of node-to-node communications.

The Q-Learning approach assists in evaluating most probable nodes for communication during handovers, which reduces node-level security. In order to improve security, a sidechain-based model is deployed. This model is useful to reduce attack probability during node-to-node communications, thereby securing the network against sybil, masquerading, and Distributed Denial of Service (DDoS) attacks. Moreover, the model for the proposed NLADSS method can be observed from Fig. 1, wherein models for making handoff decisions using dynamic sleep scheduling, sidechaining, Q-learning, and clustering are visualized. Each of these blocks are described individually in the subsequent sub-sections, which will assist readers & network designers to replicate them for their own network deployments

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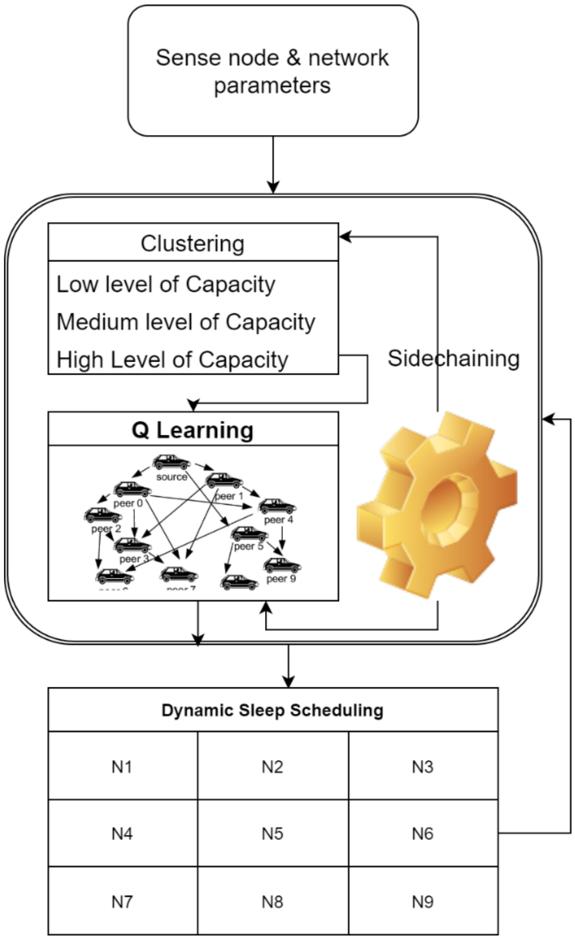

Figure. 1 Model for the proposed NLADSS method

3.1 Novel capacity-based clustering model for node-to-node assistance via augmented ranking

The capacity-based clustering model is used to facilitate better node-to-node communications, in order to maintain high QoS during routing. This consists of reducing delay, improving residual energy, reducing network jitter, and increasing throughput during transmission of data & control packets.

$$N_{R_i} = \left(\frac{\frac{N_{speed_i}}{Max(N_{speed})} + \frac{N_{velocity_i}}{Max(N_{velocity})} + \frac{Max(N_{RSSI})}{N_{RSSI_i}}}{\frac{N_{BW_i}}{Max(N_{BW})}}\right) \times \left(\frac{(N_x \times N_y)}{d(N_2B)_i}\right) \quad (3)$$

The model initially collects node & network-level data, which includes, node location, node speed, movement velocity, Received Signal Strength Indicator (RSSI), and network-specific bandwidth. Based on this information, an augmented rank value (N_R) is evaluated for each node using equation 3.

Where, $N_{speed}, N_{velocity}, N_{RSSI}, and\ N_{BW}$ indicates speed, velocity, RSSI, and bandwidth for the given node i, and Max(f) represents its maximum value. The maximum values are used in order to normalize the parameters. Moreover, $N_x, N_y, d(N_2B)_i$ represents x, y dimension of the network, and distance between node to the nearest base station, which is evaluated using Eq. (4),

$$d(N_2B)_i = \sqrt{\left(x_i - NB_{x_i}\right)^2 + \left(y_i - NB_{y_i}\right)^2} \quad (4)$$

Where, $x, y, NB_x, and\ NB_y$ indicates location of node, and its nearest base station. The calculated rank serves as a basis to find node capacity, wherein, lower ranks indicate higher capacities. These node level ranks are given to a hierarchical clustering model, for segregation of nodes into low, medium and high-capacity ranges. The clustering model works as follows,

- Initialize 3 random centroids using Eqs. (5) to (7),

$$C_1 = rand(0, min(N_R)) \quad (5)$$

$$C_2 = rand\left(min(N_R), \frac{\sum_{i=1}^{N_N} N_{R_i}}{N_N}\right) \quad (6)$$

$$C_3 = rand\left(\frac{\sum_{i=1}^{N_N} N_{R_i}}{N_N}, \max(N_R)\right) \quad (7)$$

Where, N_N represents number of nodes in the network.

- Based on these initial centroids, a difference value is evaluated for each node using Eq. (8),

$$D_{i,j} = N_{R_i} - C_j, j \in (1,3) \quad (8)$$

- Nodes are grouped into cluster j , as per condition in Eq. (9),

$$D_{c,j} = (D_{i,j} = min(D_j)) \quad (9)$$

Where, $D_{c,j}$ represents probability of node belonging to cluster j.

- Once nodes are clustered, then average of all N_R values are evaluated for a given cluster, and this average is stored as new centroids using Eq. (10),

$$C_{new_j} = \frac{\sum_{i=1}^{N_N \in j} N_{R_i}}{N_N \in j} \quad (10)$$

- This process is repeated until nodes are statically placed in the same cluster, and the centroid doesn't change.

The clustered nodes are used by a Q-learning model for improving node-to-node communications. Nodes present in higher capacity cluster, assist nodes in lower capacity cluster(s) for improving data & control signal communication. This assists in improving routing efficiency of the network. Design of the Q-learning model can be observed from the next sub-section.

3.2 Q-Learning model for intra-cluster node selection

The capacity-based clustering in the network is able to differentiate nodes depending on their capability to communicate data. This capability is utilized by Q-learning in order to facilitate high efficiency node-to-node communications. While transferring control-and-data signals from node-to-base-station, or base-station-to-node, the network inspects capacity of transmitter node, and identifies its cluster. If the node is in high-capacity cluster, then it directly participates in data-transmission without any further processing. But if the node is in either in lower band of medium or low-capacity cluster, then Q-learning model assists in selection of the most optimum node in higher capacity cluster. In order to perform this task, following Model 1 is deployed,

Model 1: To select most optimum node in higher capacity cluster

Initialization of Q-learning parameters,
- Learning rate ($\emptyset$)
- Number of iterations (N_i)
- Number of solutions (N_s)
- Discount factor (∂)
- All the solutions to be modified

for(i=1 to Ni) do

for(i=1 to Ns) do

if(*solution is marked as 'not to be modified'*)

goto next one

else

select a random node from a higher capacity cluster, and evaluate Q value using equation 11 as follows

$$Q_{new} = Q_{old} + \emptyset \times \left(R + \partial \times \left(max(Q) - Q_{old}\right)\right) \quad (11)$$

Where, $Q_{new}, Q_{old},$ and R represents new Q value, old Q value, and reward value. These 'Q' values are evaluated from Eq. (12), based on the randomly selected node.

$$Q = \left(\frac{d\left(N_{r_2}B\right)}{N_x \times N_y} + \frac{E_{max}}{E(N_r)} + \frac{J(N_r)}{J_{max}}\right) \times \frac{\sum_{i=1}^{N_c} PDR(N_r)}{N_c} \quad (12)$$

Where, $d\left(N_{r_2}B\right), E, J, PDR,$ and N_C represents distance between selected node and base-station, residual energy, jitter, and temporal packet delivery ratio of randomly selected node over N_C communications. The 'Q' value is updated for every solution, which assists in better node selection. Similarly, the reward value is evaluated using Eq. (13) as follows,

$$R = \frac{N_{R_{random}}}{N_{R_{node}}} \times D_{size} \quad (13)$$

Where, $N_{R_{random}}$, and $N_{R_{node}}$ represents rank of the randomly selected node, and rank of the communicating node respectively; while, D_{size} represents size of data being communicated between the node & base station.

- After each iteration, a threshold 'Q' value is evaluated using Eq. (14) as follows,

$$Q_{th} = \frac{\sum_{i=1}^{N_S} Q_i}{N_S} \times \emptyset \quad (14)$$

- Solutions with 'Q' values less than threshold are marked as 'not to be changed', and other solutions are marked as 'to be changed'.
- At the end of the last iteration, solution with minimum 'Q' value is selected, and the given node is used for routing.

The use of 'Q' learning, nodes are selected based on their capacity, end-to-end communication delay, residual energy, jitter, temporal packet delivery ratio, and communicated data size. This assists in selecting the best communication route, thereby improving QoS, while enhancing communication efficiency of the network. Once the path is selected, then a dynamic sleep scheduling model is applied for improving handoff quality. This model is described in the next sub-section of this paper, and assists in energy conservation via offloading major handover decisions to Road Side Units (RSUs).

3.3 Dynamic sleep scheduling (DSS) to improve handoff quality

Depending upon contextual network conditions, handovers are either node-initiated, or network-initiated. In both cases, evaluation of most optimum network for the given node is performed via parametric checks. During node-level handover initiations, parameters including bandwidth, data rate, RSSI, location, speed, and network interest are evaluated. These parameters are given to a decision engine which evaluates whether the requesting node requires handoff or not.

In such a case, if decision unit evaluates that handover must be not be performed, then the requesting node resends handover requests periodically. Due to this continuous-request-response model, the RSU's capacity is inherently reduced, which reduces network QoS, and reduces handoff efficiency. Moreover, this efficiency also reduces during network-level handover initiations, when the handoff-node is not ready, or is in sleep mode. To remove these drawbacks, a Dynamic Sleep Scheduling (DSS) model is deployed. The DSS model utilizes node rank in order to estimate wake-up and sleep cycles of nodes. For each node j, the wakeup time is controlled using Eq. (15),

$$T_{W_j} = T_{TC} \times \frac{N_{R_j}}{N_{R_j} + N_{R_{sel_j}}} \tag{15}$$

Where, T_w, and T_{TC} represents node's wake up time, and total cycle time, while $N_{R_{sel_j}}$ represents the node selected using Q-Learning. If a node is in lower capacity cluster, then the value of N_R for that node will be lower, while its partner node (the one selected via Q-Learning), will have larger value of $N_{R_{sel}}$, thereby considerably reducing its wakeup time. Similarly, the higher capacity node will have higher wakeup time, thereby assuring that either the current node, or its partner node are always in wakeup state. During network level handoff initiations, the network always inquires higher capacity nodes. If the handoff request is meant for this higher ranked node, then it is directly accepted. But if the request is for its partner node, then the partner (lower capacity node) is woken-up, and handoff request is accepted.

In case of node-level initiations, the lower capacity node sends request to the partner node, and follows its sleep cycle. The partner node (higher capacity node) keeps a track of this request, and pings the Road-Side-Unit (RSU). The RSU utilizes notification channels to inform requesting nodes about handover status, which assists in reducing power consumption. Moreover, RSUs response is forwarded to the lower capacity node, only if handover is needed, otherwise the lower capacity node maintains it sleep cycles.

The partner node changes on every communication request, thereby changing sleep cycles of all nodes. These cycles are controlled by the proposed Q-learning model, thus are dynamic in nature. Due to these dynamic cycles, partner nodes are changed during each communication. This causes data dissipation via a wide number of nodes, which introduces security loopholes in the system. These loopholes can assist an attacker node to inject sybil, masquerading, DDoS, and other types of attacks.

To reduce the probability of these attacks, a blockchain-powered sidechain model is designed & discussed in the next sub-section, which introduces immutability, traceability, and trustability to all network communications. Moreover, Q-learning, and dynamic sleep scheduling models are trained on the RSU, thereby providing high speed Connectivity as a Service (CaaS) to the vehicular nodes.

3.4 Design of the sidechain model for attack resilience

The proposed sidechaining model uses smart contracts & a machine learning layer to control sidechain creation & management. The used data storage format can be observed from Table 2, wherein entities like previous hash, source address, destination address, etc. are stored.

The storage structure can be used to store any kind of data & control signals in the blockchain. While storage, the following delays are incurred,

- **Mining delay:** It involves the time required to generate a nonce number for unique current hash values (D_{mining})
- **Hashing & encryption delay:** It ensures high security & privacy to the system (D_{HE})

Table 2. Data storage structure of the proposed sidechain

Component	Description
Prev. Hash	Hash of the previous block
Destination Address	Receiver node's address (can be IPV4, or IPV6)
Current Hop Address	Address of the current node (where data is routed)
Data for communication	Actual data or control signals being communicated
Timestamp	Data Generation Timestamp
Nonce number	A random number which insures uniqueness of this block
Source Address	Address of the source node
Source Partner Node	Address of current partner of the source node (controlled by Q-Learning)
Hash of current block	Hash (SHA512) of the current block

- **Verification delay:** It involves dissipation of data to other nodes, and gathering their consensus (D_{diss})

The hashing and encryption delay can only be reduced if lower complexity models are used, which reduces overall network security. Moreover, this delay is infinitesimal when compared with dissipation & mining delays, which increase exponentially with an increase in chain length. An increased chain length causes storage & management issues as well. Thus, sidechains are formed, and controlled using the following algorithm, which assist in reducing overall storage delay, while maintaining high network security,

- Input
  - Total learning iterations (*Nr*)
  - Total solution combinations (*Nc*)
  - Learning rate (Lr)
- To start with, mark all solutions as 'to be modified'
- For each iteration in 1 to Nr, perform the following tasks,
  - If this solution is marked as 'not to be modified', then continue to next one. Else, follow these steps,
    - Generate a random number RL, which will decide sidechain length.
    - Divide current blockchain into smaller chains of length RL.
    - Select a random chain C_{random}, and add a dummy block to this chain.
    - Investigate the mining delay, and dissipation delay for adding this block.
    - For these delay values, find solution fitness using Eq. (16),

$$f_{interm} = \frac{\left(\frac{D_{mining}}{D_{max}} + \frac{D_{diss}}{D_{max}}\right)}{2} \quad (16)$$

Where, D_{max} represents maximum delay needed to add a block to the main blockchain

    - Repeat this for all rounds, and select the sidechain combination that has minimum fitness value. This indicates that the selected sidechain selection has minimum dissipation and mining delays.
  - Perform this task for all combinations, to obtain different sidechain variations.
    - Evaluate fitness threshold using Eq. (17),

$$f_{th} = \sum_{i=1}^{Nc} \frac{f_{interm_i}}{N_c} \times Lr \quad (17)$$

    - Find combinations where fitness is more than threshold, and mark them as, 'to be changed', mark all others as 'not to be changed'
- Finally, select the sidechain length with minimum value of f_{interm} , which indicates selection of sidechain with minimum dissipation and mining delay.

Repeat this process whenever length of any sidechain crosses average length of all sidechains. Due to use of cryptographic functions, and hashing, these blocks are completely traceable, which reduces probability of Masquerading, and Sybil attacks. Moreover, in case of any tampering attacks, hash values of blocks will change, thereby discarding that sidechain, and tracking the misbehaving node.

Due to sidechain creation, DDoS attacks are also defeated, because as number of packets are injected into the system, a greater number of sidechains will be created, thus the system's performance will not degrade, and high QoS will be maintained. Network engineers can detect these larger sidechains, and traceback the source(s) of DDoS nodes. The performance of this integrated system model is described in the next section, and is observed in terms of end-to-end delay, throughput, residual energy, jitter and handoff efficiency parameters.

4. Result analysis and comparison

Due to application of Q-learning, DSS, and capacity-based clustering, overall QoS during handoffs is improved. This QoS is measured in terms of end-to-end delay, energy consumption, throughput, jitter and handoff efficiency. Moreover, due to addition of sidechaining, the model is resilient to attacks like Masquerading, Sybil and DDoS. Thus, this section compares QoS performance of the proposed model with [7, 12, 18], with and without attack. In order to enforce consistency during evaluation, each of the configurations was tested on the network simulation conditions as mentioned in Table 3 as follows.

Using this configuration, number of handoffs & communication requests were linearly changed from 20 to 200. During this simulation, stochastic modelling was done, and nodes were selected randomly for routing. Moreover, probability of attacks was varied between 1% to 20% for Masquerading, Sybil and DDoS attacks. QoS parameters were evaluated before & after attacks, and compared against [7, 12, 18].

It was observed that the proposed model was able to normalized these parameters even after attack, which indicates its attack resilience. In order

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Table 3. Network and node configurations

Parameter	Configured value
Propagation Model	Two Ray Ground
MAC Version	802.16
Interface queue (IFQ) type	Drop Tail & Priority Queue
Antenna Model	Omnidirectional
Number of vehicles	50 to 1000
Routing Protocol	DSDV
Network dimensions	0.4 km x 0.4 km
Vehicle power consumption during idle mode	2 mW
Vehicle power consumption during data reception	2 mW
Vehicle power consumption during transmission	4 mW
Vehicle power consumption during sleep mode	0.002 mW
Vehicle power required during transition from sleep to wakeup mode	0.1 mW
Delay required for this transition	0.01 s
Residual energy for each vehicle (initially)	2000 mW

to validate the analysis, this section is divided into 2 sub-parts, wherein section 4.1 indicates handoff performance without attack, and section 4.2 indicates the same performance under different attack types. Thereby assisting in evaluation of the NLADSS model under different network conditions.

4.1 QoS handoff performance without attack

The use of DSS, Q-Learning and capacity-based clustering, the proposed model showcases better handoff and QoS performance when compared with models proposed in [7, 12, 18]. In order to evaluate this performance, the number of vehicles were varied between 50 and 1000; and performance of metrics including end-to-end delay, residual energy, throughput and handoff efficiency were evaluated. Each of these node variations was accompanied with 20 to 200 handoff requests (NH), and the QoS parameters were averaged for each running cycle. This allows true estimation of performance of the underlying model, and assists in comparing its performance with the existing models. As per this evaluation strategy, end-to-end delay (D) performance for different protocols is tabulated in Table 4 as follows.

It can be observed from this tabulation that an improvement of 10% in terms of delay reduction is obtained which is mainly due to incorporation of DSS & Q-Learning.

Table 4. Average end-to-end delay for different models (50 vehicles)

No. of Vehicles = 50				
NH	**D (ms) [7]**	**D (ms) [12]**	**D (ms) [18]**	**D (ms) Proposed**
20	0.65	0.67	0.74	0.61
25	0.69	0.73	0.81	0.66
30	0.79	0.79	0.87	0.71
35	0.82	0.82	0.90	0.74
40	0.84	0.85	0.95	0.78
45	0.89	0.92	1.01	0.83
50	0.96	0.97	1.10	0.93
60	1.00	1.14	1.36	1.18
70	1.30	1.61	1.85	1.55
80	1.94	2.00	2.19	1.80
90	2.08	2.11	2.34	1.94
100	2.18	2.29	2.59	2.16
125	2.44	2.66	2.97	2.47
150	2.93	3.00	3.31	2.74
175	3.11	3.22	3.66	3.06
200	3.40	3.85	4.24	3.28

Table 5. Average end-to-end delay for different models (1000 vehicles)

No. of Vehicles = 1000				
NH	**D (ms) [7]**	**D (ms) [12]**	**D (ms) [18]**	**D (ms) Proposed**
20	0.96	0.96	1.11	0.83
25	1.01	1.05	1.21	0.90
30	1.16	1.13	1.30	0.96
35	1.20	1.18	1.35	1.00
40	1.23	1.23	1.42	1.06
45	1.31	1.31	1.51	1.13
50	1.40	1.38	1.64	1.26
60	1.46	1.63	2.05	1.59
70	1.91	2.30	2.77	2.11
80	2.85	2.85	3.29	2.45
90	3.05	3.03	3.51	2.62
100	3.20	3.28	3.87	2.92
125	3.57	3.81	4.46	3.35
150	4.29	4.28	4.96	3.72
175	4.56	4.62	5.50	4.31
200	4.99	5.51	6.36	4.45

As the number of vehicles are increased from 50 to 500, the delay performance is further optimized. An improvement of 12% in terms of delay reduction is obtained which is mainly due to incorporation of DSS, Q-Learning and use of dynamic clustering. As the number of vehicles are increased from 500 to 1000, the delay performance is further optimized. This can be observed from Table 5.

It can be observed that an improvement of 14% in terms of delay reduction is obtained due to incorporation of Q-learning, DSS & sidechaining.

Table 6. Average energy consumption for different models (50 vehicles)

No. of Vehicles = 50				
NH	**E (mJ) [7]**	**E (mJ) [12]**	**E (mJ) [18]**	**E (mJ) Proposed**
20	1.21	2.04	1.91	1.64
25	1.88	2.51	2.23	1.88
30	1.91	2.61	2.34	1.97
35	2.05	2.75	2.46	2.09
40	2.11	2.92	2.63	2.22
45	2.32	3.11	2.77	2.34
50	2.39	3.23	2.88	2.43
60	2.50	3.36	2.99	2.52
70	2.59	3.49	3.11	2.62
80	2.70	3.61	3.25	2.75
90	2.77	3.87	3.51	2.97
100	3.08	4.26	3.77	3.16
125	3.38	4.32	3.78	3.17
150	3.16	4.24	3.78	3.11
175	3.28	4.40	3.33	2.53
200	3.46	4.53	3.70	2.51

Table 7. Average energy consumption for different models (1000 vehicles)

No. of Vehicles = 1000				
NH	**E (mJ) [7]**	**E (mJ) [12]**	**E (mJ) [18]**	**E (mJ) Proposed**
20	1.77	2.92	2.87	1.95
25	2.76	3.59	3.36	2.24
30	2.80	3.74	3.51	2.35
35	3.00	3.94	3.70	2.48
40	3.10	4.19	3.94	2.63
45	3.40	4.46	4.16	2.77
50	3.52	4.63	4.32	2.88
60	3.66	4.82	4.49	3.00
70	3.80	5.00	4.66	3.11
80	3.96	5.18	4.87	3.28
90	4.07	5.54	5.27	3.53
100	4.52	6.12	5.67	3.75
125	4.97	6.19	5.69	3.76
150	4.63	6.08	5.68	3.68
175	4.80	6.31	5.01	3.00
200	5.12	6.64	5.55	3.41

Table 8. Average throughput performance for different models (averaged between 50, 500 and 1000 vehicles)

Average of 50, 500 and 1000 Vehicles				
NH	**T(kbps) [7]**	**T(kbps) [12]**	**T(kbps) [18]**	**T (kbps) Proposed**
20	223.1	212.5	249.8	286.3
25	227.6	215.0	252.2	288.8
30	228.3	215.9	253.5	290.5
35	229.4	217.7	255.7	293.1
40	232.0	219.8	258.1	295.8
45	234.0	221.7	260.3	298.3
50	236.0	223.5	262.6	300.8
60	237.9	225.4	264.7	303.3
70	239.9	227.2	266.9	305.8
80	241.9	229.1	269.1	308.3
90	243.9	230.9	271.3	310.8
100	245.8	232.8	273.4	313.3
125	247.8	234.7	275.6	315.8
150	249.8	236.6	277.8	318.3
175	251.8	238.5	280.0	320.8
200	253.7	240.4	282.2	323.3

Table 9. Average handoff efficiency performance for different models (averaged between 50, 500 and 1000 vehicles)

Average of 50, 500 and 1000 vehicles				
NH	**Eff.(%) [7]**	**Eff.(%) [12]**	**Eff.(%) [18]**	**Eff. (%) Proposed**
20	83.28	83.38	84.39	86.78
25	84.95	84.34	85.21	87.56
30	85.22	84.68	85.64	88.06
35	85.65	85.38	86.38	88.83
40	86.63	86.23	87.21	89.66
45	87.36	86.96	87.94	90.42
50	88.09	87.68	88.68	91.18
60	88.83	88.42	89.42	91.93
70	89.57	89.15	90.16	92.69
80	90.31	89.88	90.89	93.45
90	91.04	90.61	91.63	94.21
100	91.78	91.35	92.37	94.96
125	92.52	92.07	93.11	95.72
150	93.26	92.80	93.84	96.48
175	93.99	93.54	94.58	97.24
200	94.73	94.27	95.32	98.01

The reason for this delay reduction is availability of larger number of nodes in the same area, which assists in faster data routing.

Similar observations are done for energy performance, this can be observed for 50 nodes from Table 6.

It can be observed that a reduction of 9% in terms of energy consumption is obtained due to incorporation of the proposed NLADSS model.

As the number of vehicles is increased from 50 to 500, the energy consumption is further reduced, thus improving overall energy efficiency. It is observed that a reduction of 20% in terms of energy is obtained due to incorporation of the NLADSS model. This energy consumption is further reduced as the number of vehicles is increased from 500 to 1000. This can be observed from Table 7.

It can be observed that a reduction of 29% in terms of energy consumption is obtained due to incorporation of NLADSS model. The reason for this energy reduction is availability of larger number of nodes in the same area, which assists in having better network lifetime.

Similar observations are done for throughput performance, this performance is averaged for 50, 500 and 100 vehicles; and can be observed from Table 8.

It can be observed that an improvement of 16% in terms of throughput is obtained due to incorporation of the proposed NLADSS model. The reason for this throughput improvement is use of QoS related parameters during partner node selection.

Similar observations are done for handoff efficiency performance, this performance is averaged for 50, 500 and 100 nodes. This is done such that the network performance can be evaluated for low, medium and large number of nodes; and can be observed from Table 9.

It can be observed that an improvement of 4% in terms of handoff efficiency is obtained due to incorporation of the NLADSS model.

The reason for this packet delivery ratio improvement is use of sidechaining, DSS and hierarchical clustering. These evaluations are extended for different number of attacks in the network, and can be observed from the next section.

Due to these observations, the proposed model is superior in terms of handoff efficiency, and QoS performance with and without attacks. This makes the proposed model applicable for a wide variety of vehicular network scenarios.

5. Conclusion and future scope

The Q-Learning works on a reward function, which assists in selecting the most optimum node partner for any given node. This when combined with dynamic sleep scheduling, and hierarchical clustering further assists in improving overall handover performance. But this performance is limited by the security gaps, which are injected due to use of dynamic partner node. Thus, to enhance overall security, this paper proposes design of a machine learning sidechaining model.

As a result of these models, the underlying system model is capable of reducing end-to-end delay by 8% to 15% depending upon network configuration, further, it reduces energy consumption by over 14% when compared with [7], [12], and [18], thereby indicating better network lifetime. Moreover, the model is observed to outperform existing methods in terms of throughput, and overall handoff efficiency, which is mainly due to combination of DSS, Q-Learning & dynamic clustering approaches.

The model can be extended to assists in reducing probability of network attacks, which is due to inclusion of sidechain-based data storage and communication capabilities. The model's performance can be further improved via exploration of newer blockchain consensus models that require lower complexity, and the machine learning process can be further fine-tuned via use of hyperparameter tuning.

Conflict of Interest Disclosure Form

I/We certify that there is no actual or potential conflict of interest in relation to this article.

Author Contributions

The article "NLADSS: Design of connectivity as a service (CaaS) model using node-level augmentation & dynamic sleep scheduling for heterogeneous wireless network handoffs".

The research work is done by the corresponding author, Mr. Prasanna Kumar G, Research Scholar under the supervision and guidance of Dr. Shankaraiah, Professor, SJCE College of Engineering, Mysore.

conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, Mr. Prasanna Kumar G; supervision, Dr. Shankaraiah; project administration, Dr. Shankaraiah;

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