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A Novel Handover Method Using Destination Prediction in 5G-V2X Networks

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A NOVEL HANDOVER METHOD USING DESTINATION PREDICTION IN 5G-V2X NETWORKS

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ABSTRACT

This paper proposes a novel approach to handover optimization in fifth generation vehicular networks. A key principle in designing fifth generation vehicular network technology is continuous connectivity. This makes it important to ensure that there are no gaps in communication for mobile user equipment. Handovers can cause disruption in connectivity as the process involves switching from one base station to another. Issues in the handover process include poor load management for moving traffic resulting in low bandwidth or connectivity gaps, too many hops resulting in multiple unneccessary handovers, short dwell times and ineffective base station selection resulting in delays and other connectivity issues. Here, we propose an efficient handover model using trajectory prediction and optimized target base station identification.

Index Terms: **Machine Learning, Cell Selection, 5G, Vehicular Networks, Handover**

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I. INTRODUCTION

The fifth generation (5G) of wireless network technology has a rich feature set that is centered around good connectivity and high data rates. It supports versatile applications and integration. Some concepts around 5G technology include Software Defined Networking (SDN), Massive Multiple-Input MultipleOutput (MIMO), Network Function Virtualization (NFV), smaller, denser networks and mmWave Communication in small base stations. It capitalizes on the large bandwidth and capacity provided by the combination of mmWave technology and Ultra Dense Network (UDN) architecture. In the case of small base stations deployed in an Ultra Dense Network, the capacity and high data rates come at a cost. Mobility is a majorly impacted area. Since the coverage of the base stations is over a small area, it can lead to frequent handovers and short dwell times on any single base station. A direct consequence of frequent handovers is the overhead involved and also the increase in latency due to mobility.

The Random-Access Channel (RACH) configuration process as given in fig. 1 consists of the transfer of measurement reports from User Equipments (UE) to the network and the handover decision being made. The measurement report includes values of the Reference Signals Received Power (RSRP), Reference Signals Received Quality (RSRQ) and the Signal to Interference plus Noise Ratio (SINR) sent by the user equipment to the current base station that it is connected to. Once the UE sends this singal information, the current base station assigns the RACH resources. The Radio Resource Control (RRC) reconfiguration happens when the corresponding message is sent to the UE and the UE connects to the target base station. Vehicular networks need to deal with constant changes in the network topology. When dealing with high speeds and dense networks, it becomes increasingly challenging to ensure continuous connectivity. 5G Vehicular-to-everything (V2X) networks are device centric in the way that peer-to-peer communication in say platoons, Road Side Units (RSUs) and other nodes within the environment is prevalent. All entities involved in the vehicular network constantly communicate and transfer data about things like the environment and road conditions, traffic data and information about other vehicles in the vicinity. Since mobility is an important aspect of vehiclular networks, in order to ensure that the vehicle stays connected at all times, an efficient handover mechanism is important. The current research in vehicular networks, particularly for handovers in vehicular networks leverage the rich feature set provided by 5G New Radio. Conventional base station selection algorithms use signal parameters such as the RSSI, RSRP, RSRQ and other values in order to make a decision. Using a single parameter such as the RSRP or RSRQ values will not work in 5G Vehicular networks owing to small, dense networks, high speeds and the presence of buildings and other obstacles that impact the network topology. Using conventional algorithms can result in unneccessary handovers, interruptions in connectivity, short dwell times and bad load distributions. This research attempts at finding a better base station selection algorithm using destination prediction.

II. RELATED WORK AND CONTRIBUTIONS

The 5G-V2X infrastructure change has multiple implications, one of the biggest being the need for optimized handover algorithms. There are different parameters to optimize for. One could optimize for the number of handovers for a given route, for the frequency of handovers, the dwell time on a particular base station and so on. The parameters to consider while optimizing handovers include Received Signal Strength Indicator (RSSI) and Signal to Interference and Noise Ratio (SINR) values, channel bandwidth, Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ) values, distance from base stations, the velocity of the vehicle, the direction of movement and the presence of buildings and other obstacles that affect interaction and signals. There is a good amount of research and findings in the case of handovers in 5G-V2X networks. In this section we will look at the existing relevant literature and how it pertains to the proposed handover method.

2.1 Related Work

[2] talks about methods of base station selection for platoons. The 5G V2X architecture has small base stations and large base stations. The small base stations have smaller ranges and are used to eliminate dead angles in the areas covered by large base stations. An efficient handover algorithm is important and the results are based on simulations of communication between base stations and vehicles, signals, velocity of vehicles and platooning. They use deep learning for creating a model that optimizes handovers for platoons. They directly model handover parameters to correlate to model parameters. For example, the agent is the entity that learns and

makes the decision to start a handover, the environment includes the speed, direction and other variables and the state is the base station selected. The goal is the best way for the platoon to select the next base station. [3] is a detailed, comprehensive guide to understand the new V2X standard based on the 5G New Radio interface. It gives information on the architecture and the system design to go deeper into the standard. They also provide some insight into possible work that can be done to make a richer feature set.

[4] Explores the X2 interface for handover in V2X networks. This looks at it from a Software Defined Networking standpoint and propose an approach to improve the handover preparation time and the handover completion time itself. In an X2 based handover the source and target eNBs are connected to the same Mobility Management Entity (MME). They provide results that show the improvement as compared to a baseline. They run their experiments with a simulator built on top of the tool, NS3. [5] looks at a new scheme that allows dwell time estimation in Ultra Dense Newtorks (UDN) commonly found in 5G-V2X infrastructure. They use datasets containing vehicle information as well as 5G small cell location data in the city of LA. We use the latter to run our simulations. They talk about how the older cell selection strategies focus on the nearest base station with the highest RSSI values as the most probable candidate base station to handover to. They estimate the dwell time as a function of distance between the vehicle and the base station, and the direction of movement of vehicle with respect to the base station.

- Handover algorithm implemented based on RSRQ measurements.
- Detect neighboring cells and their RSRQ values.

We have two conditions that need to be met for this to work. The first condition is that the serving base station's RSRQ falls below a threshold. The second condition is that a neighboring cells RSRQ is better by a certain offset. The handover is triggered when both conditions are met.

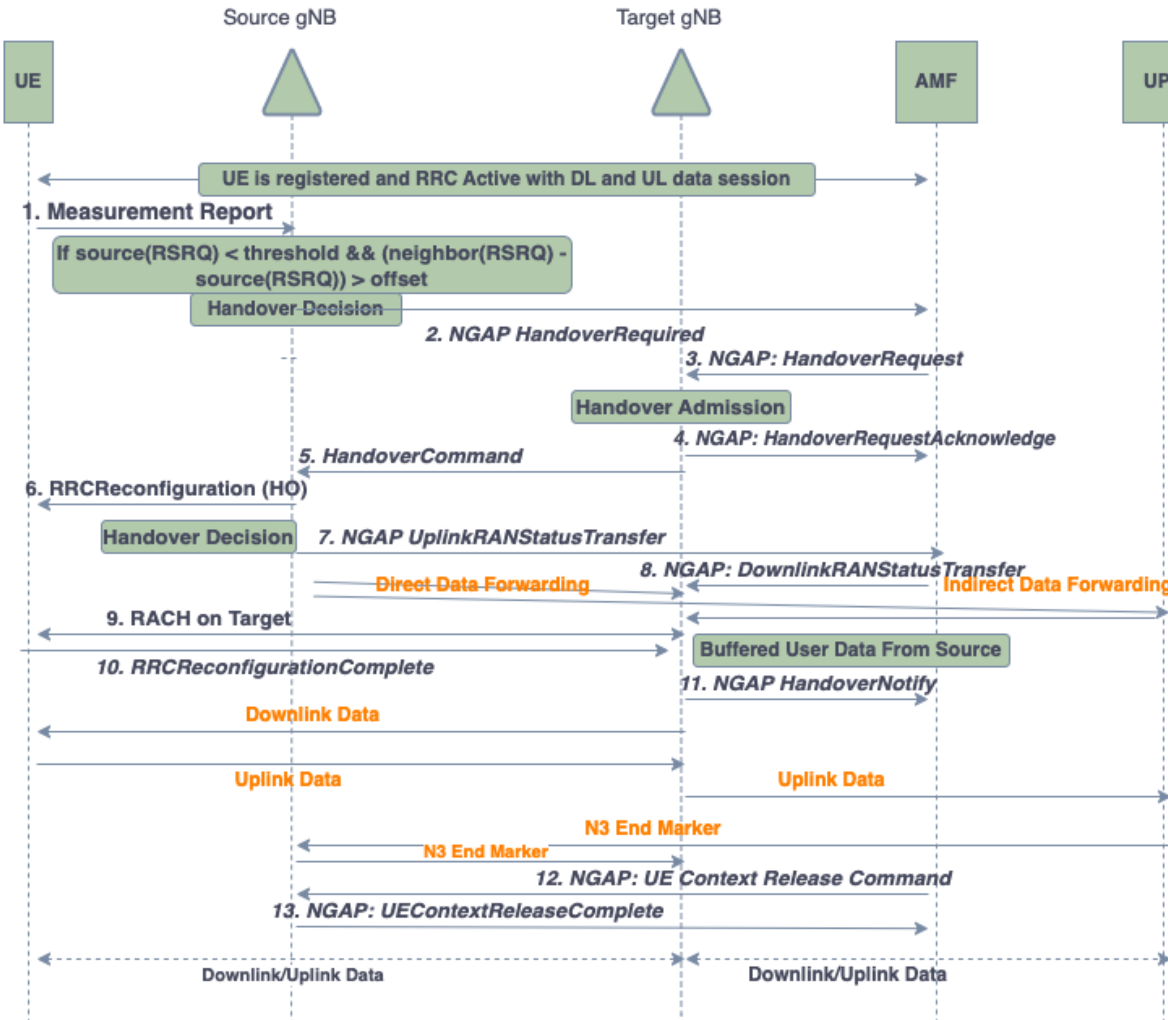

Fig 1: The Baseline Handover Process

2.2 Contributions

The contributions of this paper are as follows:

- Based on the observation that people tend to follow the same routes regularly, we use machine learning to develop a model based on vehicle mobility data. This model predicts the destination given the current location and time of the day. The destination location is used to construct the base station selection mechanism.
- We propose a way to select the target base station given the destination of the vehicle and real world small cell locations. The base station selection algorithm factors into account the RSSI values, velocity of the vehicle, distance and load to formulate a optimized route

with minimal hand-offs. We experiment with a formula, optimizing the handover algorithm based on distance and load.

- We simulate the handover using SUMO with NS3 and model the network and propagation model on real world scenarios with mmWave communication and small cell Ultra Dense Networks based on data provided by the LA city website.
- We experiment with different parameter sets for handover simulation and compare a baseline algorithm that comprises a handover mechanism using RSRQ values to the proposed algorithm.
- We define metrics for performance measurement for ensuring an accurate comparision between the baseline and the proposed algorithm.

III. PROPOSED ALGORITHM

The proposed algorithm has two parts. The first part is the destination prediction for the vehicle. The second part is the base station selection.

3.1 Destination Prediction

Historical data of vehicular mobility is generated for a selected region in the city of Los Angeles, California. The mobility is modeled after real traffic data obtained from Google maps. The data set consists of date, time, vehicle ID and the start and end locations. A predictive model is constructed wherein, the destination location can be predicted given the date, time and start location for a vehicle. We experiment with knearest neighbors and random forests and pick the best performing model for the given data. For destination prediction using machine learning, the dataset used consists of timestamp, xStart, yStart, xEnd and yEnd. This data is derived from the SUMO traces and is integrated with the dataset from [9] to achieve more localization for the prediction. The SUMO traces are generated over a specific region in LA so the more localized trip data that is added to the model, the better it will perform in that region. We use the method mentioned in [9] with slight modifications. We use the x and y coordinates used in sumo as is because it gives a relative not absolute positioning method. We also group time of the day into 3 bins - morning, afternoon and evening. So any timestamp is binned into the closest value. Morning is arbitrarily taken as 7:00AM, Afternoon is 1:00 and evening is 6:00. Traffic is seen to reduce during the night and hence the timestamp values that occur during the night are binned into the closest (morning or evening) buckets. There is no apparent linearity in this dataset. None of the features can be linearly extrapolated in order to predict the destination location. The k-nearest neighbors is a relevant choice because it predicts the destination based on the k closest patterns seen in the data. A key aspect of a vehicle destination prediction model is that it won't generalize well unless we have data of multiple locations. So here, we localize the model by training it on LA specific data to make it more accurate for the purposes of the algorithm. Random forests could work pretty well here as they can deal very well with unbalanced and localized datasets. The idea here is that a set of weak learners can be combined to form a strong learner. To tune the model, we look at the effect of the set of features picked on the accuracy of the model. We use grid search cross validation to fit and score parameter sets and figure out which parameters work the best. We use the RMSE value to determine how the model is doing. If the accuracy of the model is good, we get a reasonable estimate of the straight line trajectory of the vehicle from start to end. We can use that to optimize the handover algorithm and that is detailed in the next section. The machine learning model used in this scenario gets more accurate as more localized data is provided. The number of features we begin with are few. A lot of the machine learning models reviewed have multiple features to consider. We focus on derivative features and on how to achieve a good accuracy with few important features. We base the model on the research given in [1]. This is how we chose k-NN.

3.2 Base Station Selection

Once we have the destination location, we construct a graph of candidate base stations that are 'along' the path to the destination. This is done in the following way:

Let the start location be (x_1, y_1)

$$slope(m) = \frac{y_2 - y_1}{x_2 - x_1} \tag{1}$$

using

$$y - y_1 = m(x - x_1) \tag{2}$$

we can formulate a path equation from start to destination. Once that is done, we find the perpendicular distance of base stations located within an area of 30 degrees on either side of the direction of movement of the vehicle. If the location of the base station is at (x, y) and the path is $ax + by + c = 0$, the perpendicular distance to the path is

$$D = \frac{|ax_1 + by_1 + c|}{\sqrt{a^2 + b^2}} \tag{3}$$

We have a predefined load on each base station that is based on the density of vehicles in that area at a given time. Let the load be constant for each base station at a given time and be denoted by L. We formulate an equation to select a base station as a function of distance

$$f(distance) = w_1 * distance + w_2 * L \tag{4}$$

where w1 and w2 are weights optimized for selection of the best target base station. Using trial and error we found that when $w1$ = 0.0337 and $w2$ = 0.0117, we get the best results. We compare how the model performs for both equations. Here, we are trying to minimize the value of the cost function f. The base station with the least value of f is chosen.

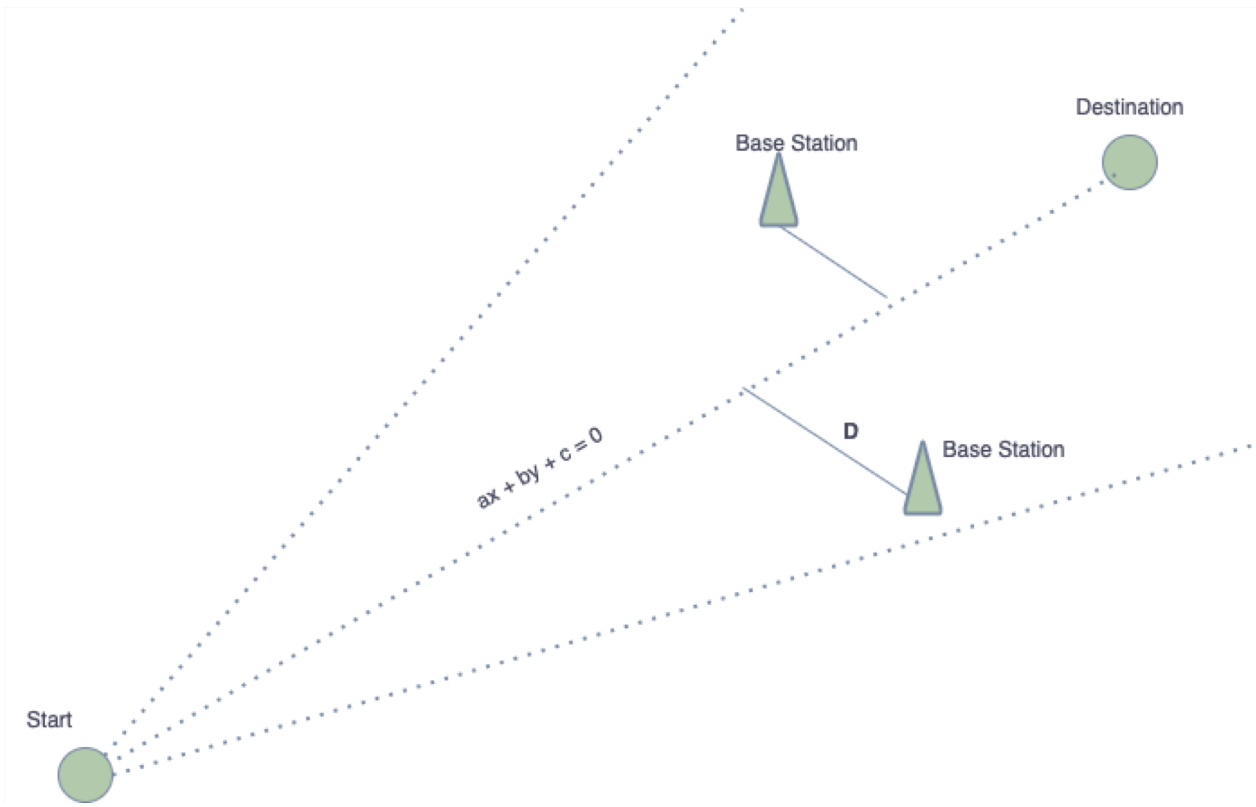

Fig. 2: Distance function

IV. SIMULATION FRAMEWORK

We have used the Los Angeles small cell 5G dataset published by *data.LAcity.org*.

This is the official website for the city of Los Angeles. It contains the identification number and the latitude and longitude of 5G small base stations in the streets of LA. These are scattered through multiple areas of the city and are attached to street light infrastructure. The mobility model used involves a mobility trace obtained using the Simulation of Urban Mobility (SUMO) tool shown in fig. 2 from OpenStreetMap data as shown in Fig. 1 for a section of the city of LA.

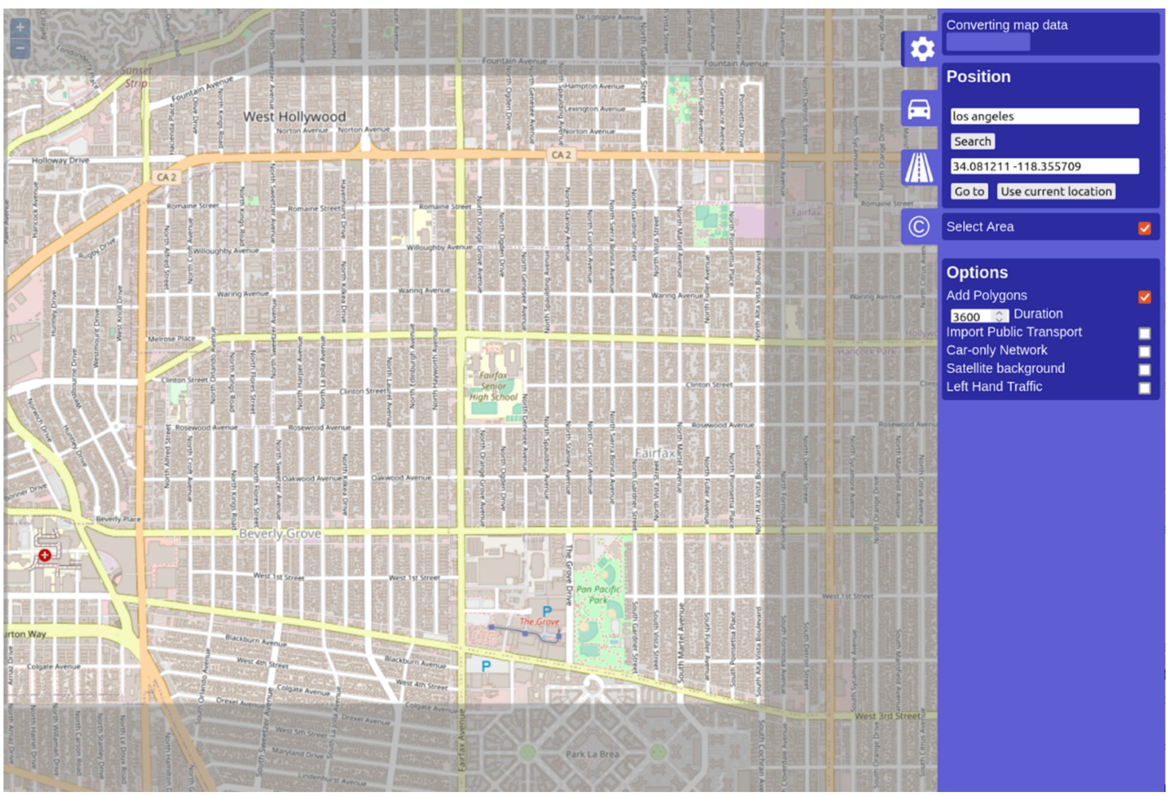

Fig. 3: Open Street Map Area Selection

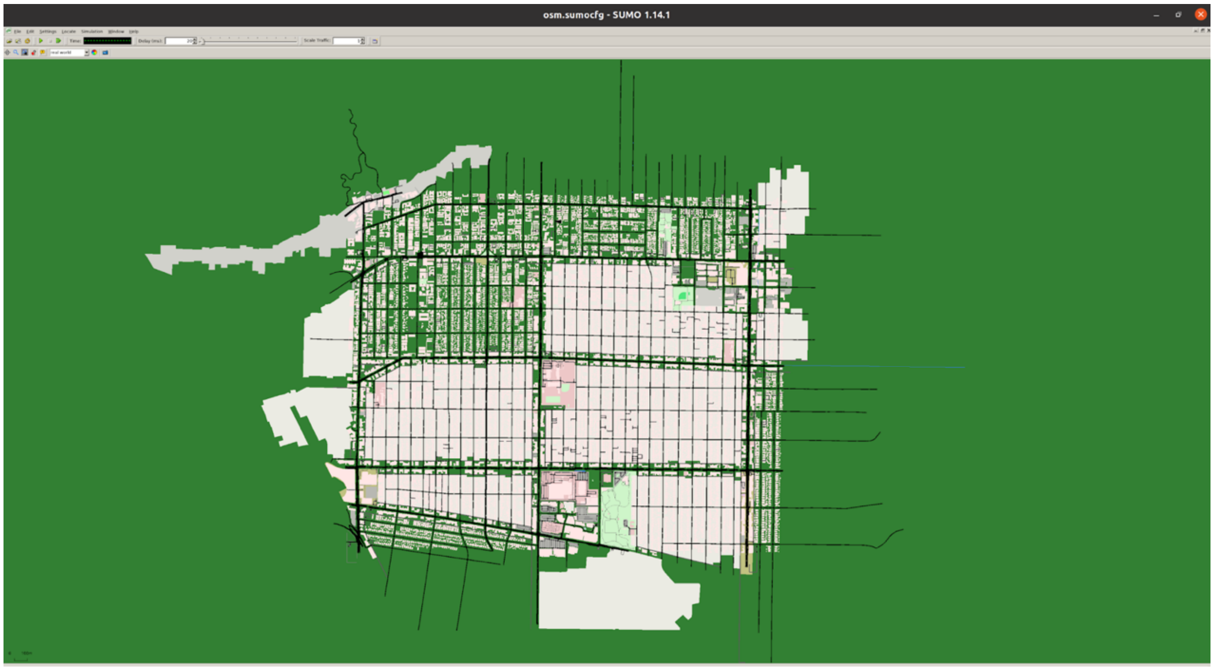

Fig. 4: Conversion of map data in SUMO

We use the log distance propagation model for modelling the reception power given by $L = L0 + 10*n*\log(d/d0)$, where L is the Path loss (dB), d is the distance from the base station, L0 is the path loss at the reference distance (dB), d0 is the reference distance (m) and n is the path loss distance exponent.

SUMO allows the modeling of automated driving, the simulation of vehiclular network communication, the control of simulated traffic including adding speed limits, modelling traffic light behavior and so on. It allows importing topologies from popular mapping and network tools like OpenStreetMap. The tool is open source and freely available. Network Simulator 3 (NS3) is a popular tool in communication networks research. It allows the simulation of network traffic, node mobility, protocol stack modelling, channel modification and so on. It allows capturing logs at the packet level as well as at the communication channel level.

Integrating SUMO with NS3 requires some intermediate work to be done. In order for the mobility trace obtained in SUMO to be used in NS3 we need to create a .tcl file that can be read and parsed correctly. This mobility.tcl file contains details about the traffic simulation, the number of entities in the simulation, the network topology, the speed and locations of vehicles at different points in time and general movement information. We use a script called osmWebWizard.py that is included in the SUMO tool that converts the OpenStreetMap data into a format readable by SUMO. Once we have this data, we can run a program included with NS3 called ns2-mobility-trace.cc that converts this data into a file that can be parsed by NS3.

We can visualize the mobility using the NetAnim tool. It involves adding the import and running the visualization itself and it works to get a graphic illustration of what the algorithm is doing. NS3 provides a rich feature set of perfomance metric capture tools. It has integrations with tools like wireshark and tracemetrics as well as tools and libraries for plotting the values captured. In the code itself, the vehicles as well as base stations are modelled as nodes. We create a NodeContainer for each kind of node and specify the number of them we need. For the logs and metrics we capture the base station information during a handover along with timestamp values. We log each time a handover takes place. The performance metrics in our case are the dwell times and the number of handovers. This can be easily inferred through the logs and the timestamp values.

The LENA mmWave module is used in conjunction with NS3 to simulate the handoff and for the performance metrics. In the code, each RSU is identified by a 16 bit integer cell ID. The user equipment is identified by the International Mobile Subscriber Identifier (IMSI) number and the Radio Network Temporary Identifier (RNTI). The baseline algorithim works by maintaining a list of candidate base stations to handover to. The base stations that are closer to the user equipment and have higher RSRQ values are considered for deciding the target base station. We run the simulation for three routes spanning different total distances travelled by the vehicle. The vehicle changes velocity randomly throughout the simulation the maximum velocity achieved is 40 miles per hours as this is a residential part of Los Angeles. The mobility models are created in SUMO and are exported into NS3. The mobility models are created using SUMO's integration with Open street maps that allows the simulation over specific locations. Once we import the mobility models into the NS3 tool, we add the base station topology . In the area we simulate, there are around 20 base stations. These are simulated as mmWave small base stations and the handovers as the vehicle moves are captured.

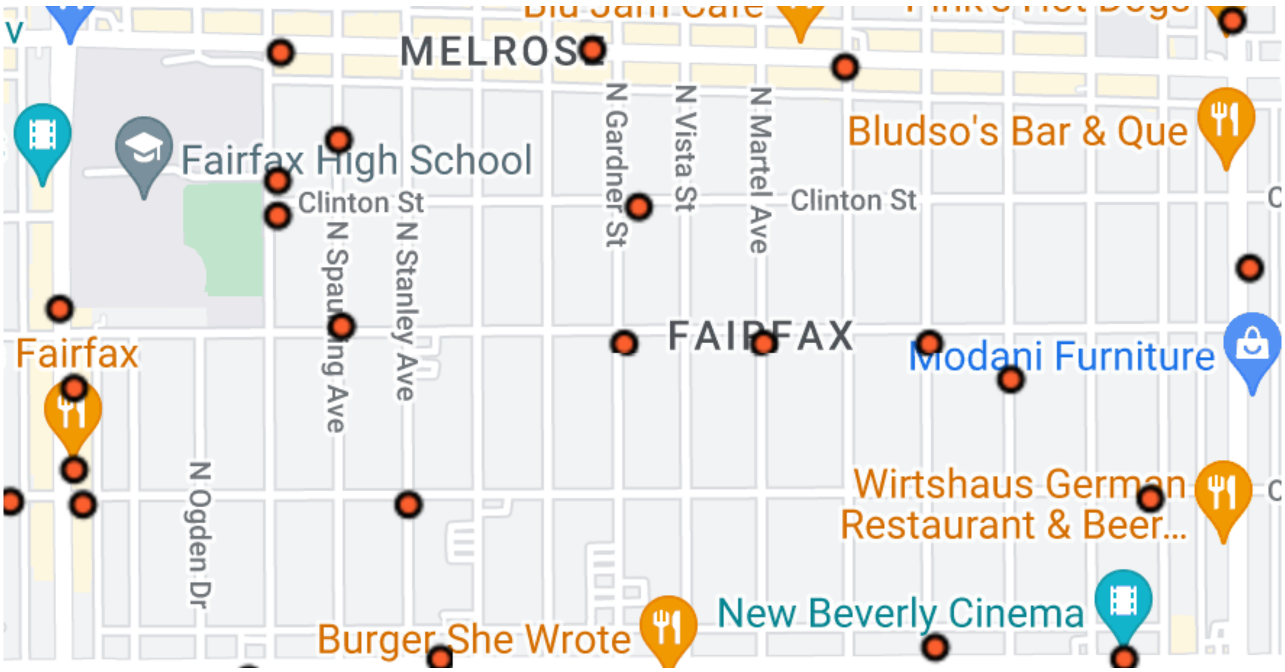

Fig. 5: Base station locations.

The figure shows a plot of the base station locations in the area being simulated. As you can see, it is not a uniform distribution. In the area being simulated, all the routes are associated with atleast 15 of the same base stations. Meaning, at some point in the route, most of the base stations are considered as a candidate target at some point. So the non-uniformity evens out for this particular area because it is small (around 10 mi x 10 mi). As given in the future work section, there is scope for further experimentation in a larger area taking into account the uniformity of base station distribution. The algorithm is simulated as running on the network side (not on the UE) and it is assumed that there is a global state that is maintained for the purposes of simulation.

V. RESULTS

The performance of the proposed model is measured by baselining and comparing the number of hand-offs and the mean dwell times. We run the experiments for three routes of different lengths in the same area in Los Angeles. The simulation time of route 1 is 10 minutes, route 2 is 50 minutes and route 3 is 15 minutes. The results of the machine learning model are as follows: The accuracy score for localized data is as follows: R2(train) = 0.993232 and R2(valid) = 0.998291 The RMSE(train) = 0.391814 and the RMSE(valid) = 0.43740. Given this accuracy in the prediction of the destination of the vehicle, we have a high probability of getting the most optimal selection for the base station based on the route taken. The dwell time is calculated as follows:

$$D = \frac{t_1 * D_1 + t_2 * D_2 + t_3 * D_3}{t_1 + t_2 + t_3} \tag{6}$$

and the overall average dwell time is calculated using the average dwell times for each of the routes. The weighted averaged over all of the routes gives D. Here, D_1, D_2, and D_3 represent the average dwell times for each route. t_1, t_2, and t_3 are the simulation times (in minutes for each route). This is an good indicator of the average dwell time for any given route in that section of Los Angeles.

The Cumulative Density Function (CDF) and the Probability Density Function (PDF) of the average dwell times for route 1 is given below. As we can see, there is a significant increase in the average dwell time. We use the CDF plot to describe the probability density cumulatively, over the time taken to simulate the route. This gives an idea of the probability of the dwell time being a certain value less than or equal to the current value at any point in the graph. The first six graphs depict the CDF and PDF plots of the dwell times on the base stations for each of the three routes.

The x – axis in these plots denotes the serial number of the datapoint. The xth dwell time. The y value is the probability density, not the probability (so it can be greater than one).

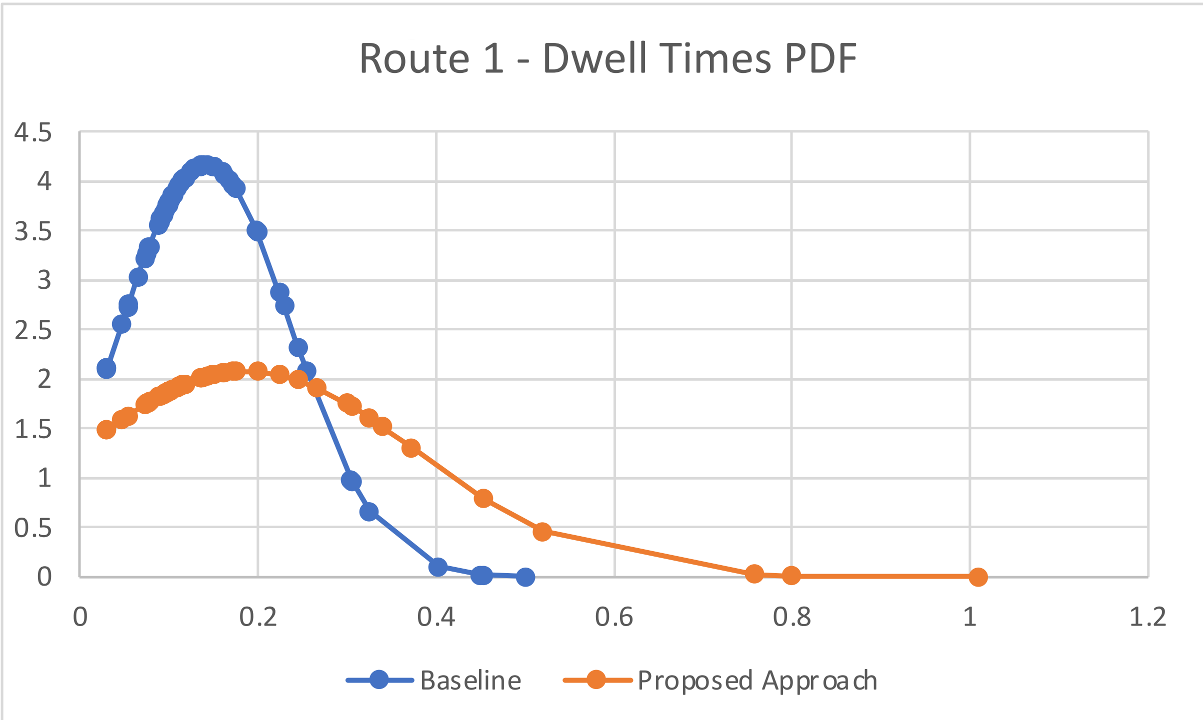

Fig 4: Route 1 Dwell Times PDF

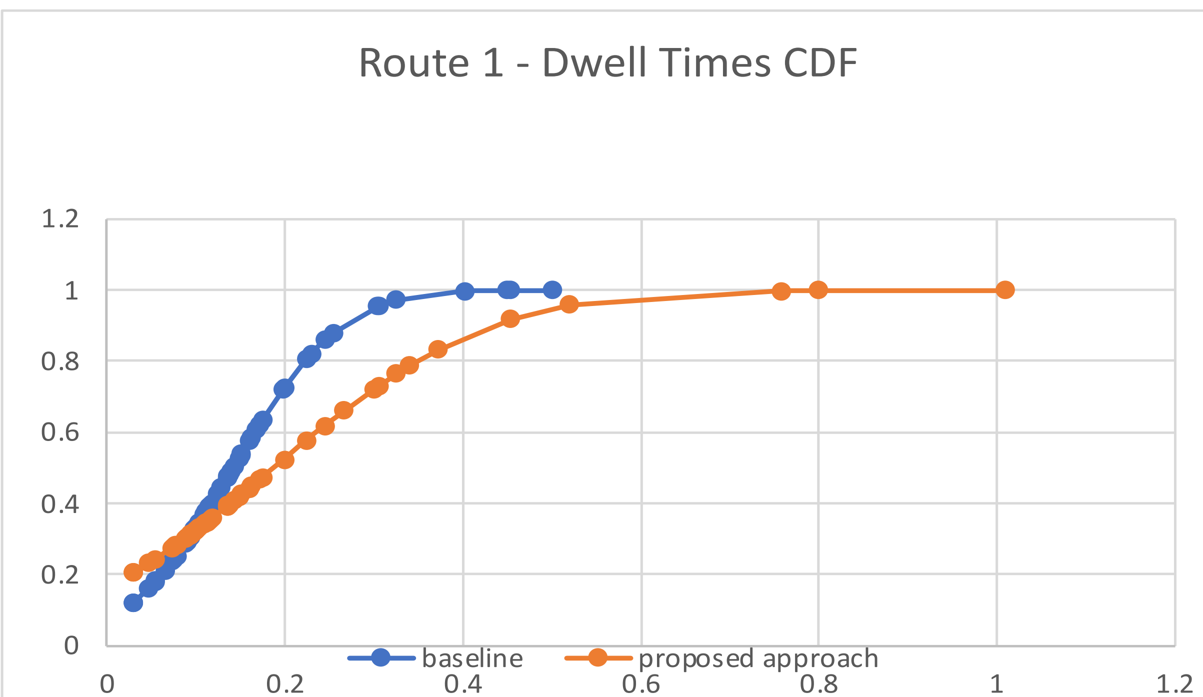

Fig 5: Route 1 Dwell Times CDF

The average dwell times for route two is depicted as CDF and PDF values in fig. 6 and fig. 7. We can see a significant increase for the second route as well.

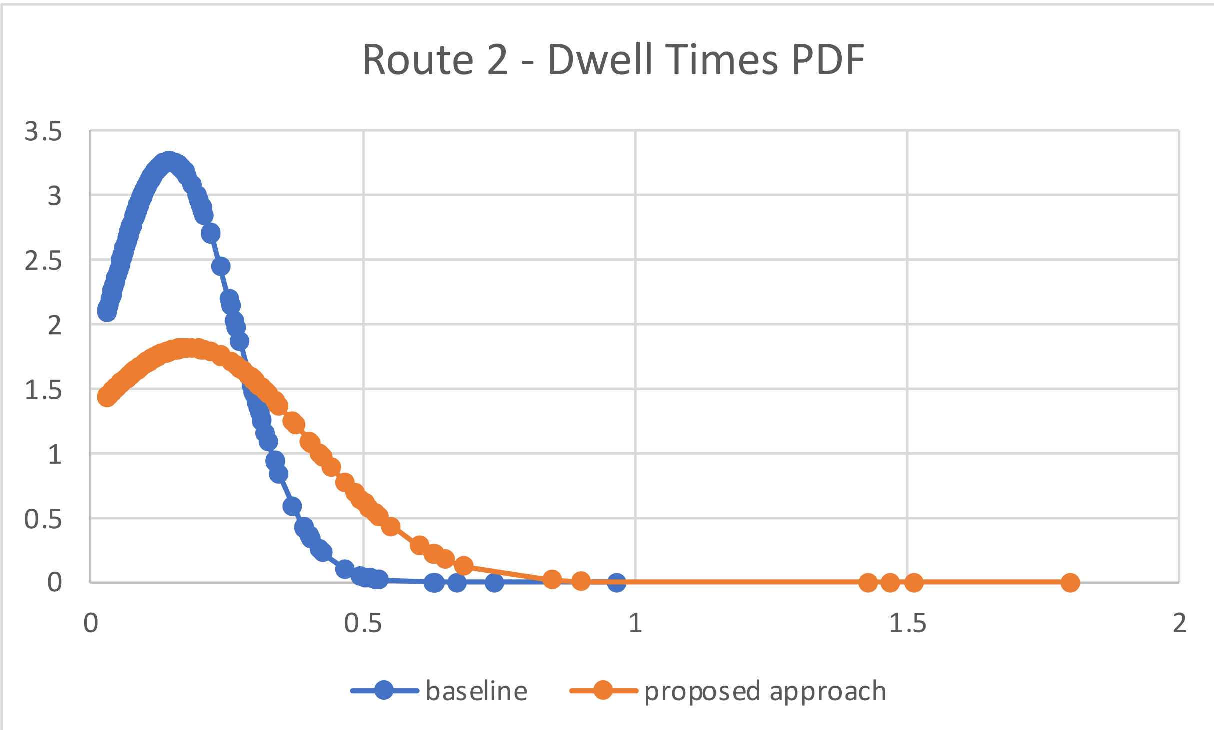

Fig 6: Route 2 Dwell Times PDF

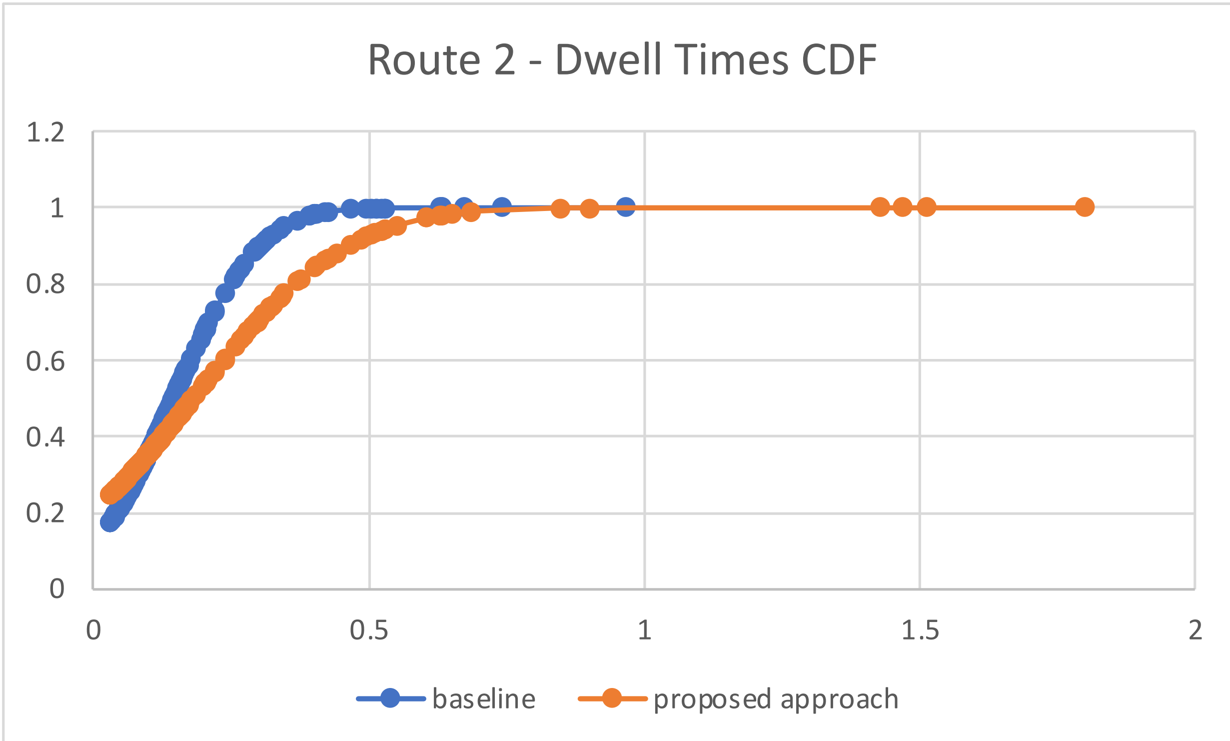

Fig 7: Route 2 Dwell Times CDF

We can also see an improvement in the dwell times for the third route as given in fig. 8 and fig. 9.

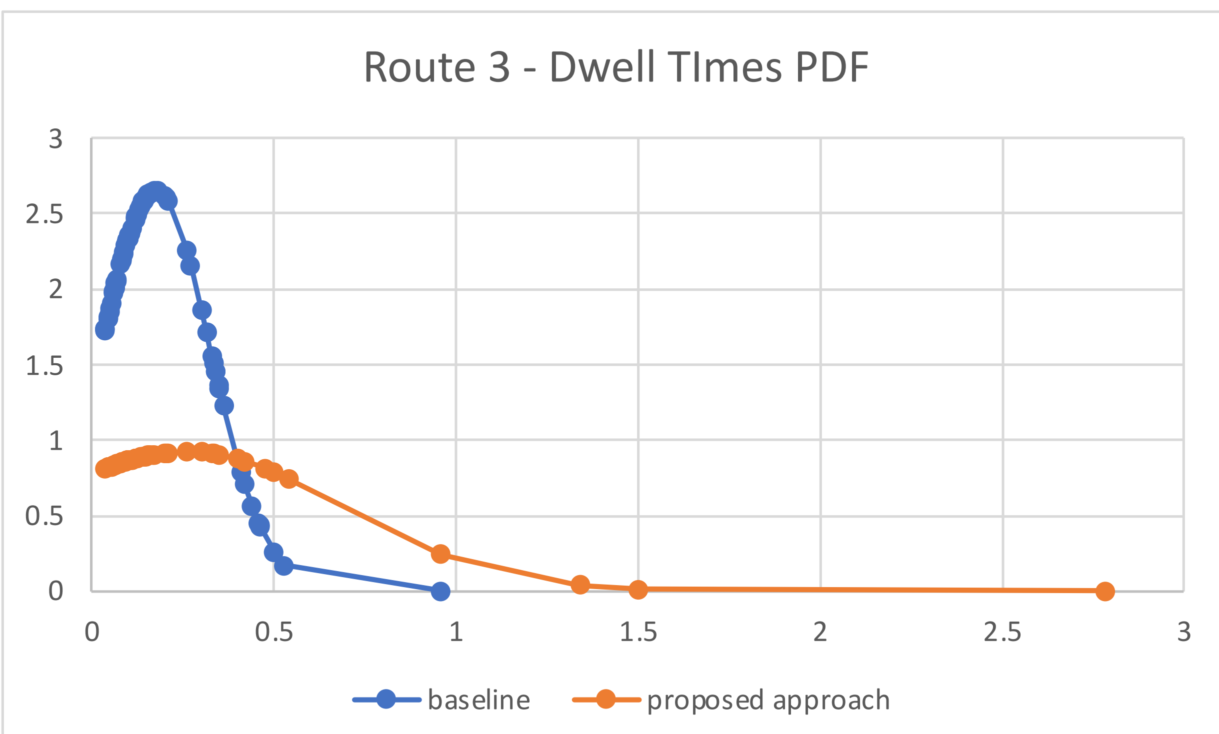

Fig 8: Route 3 Dwell Times PDF

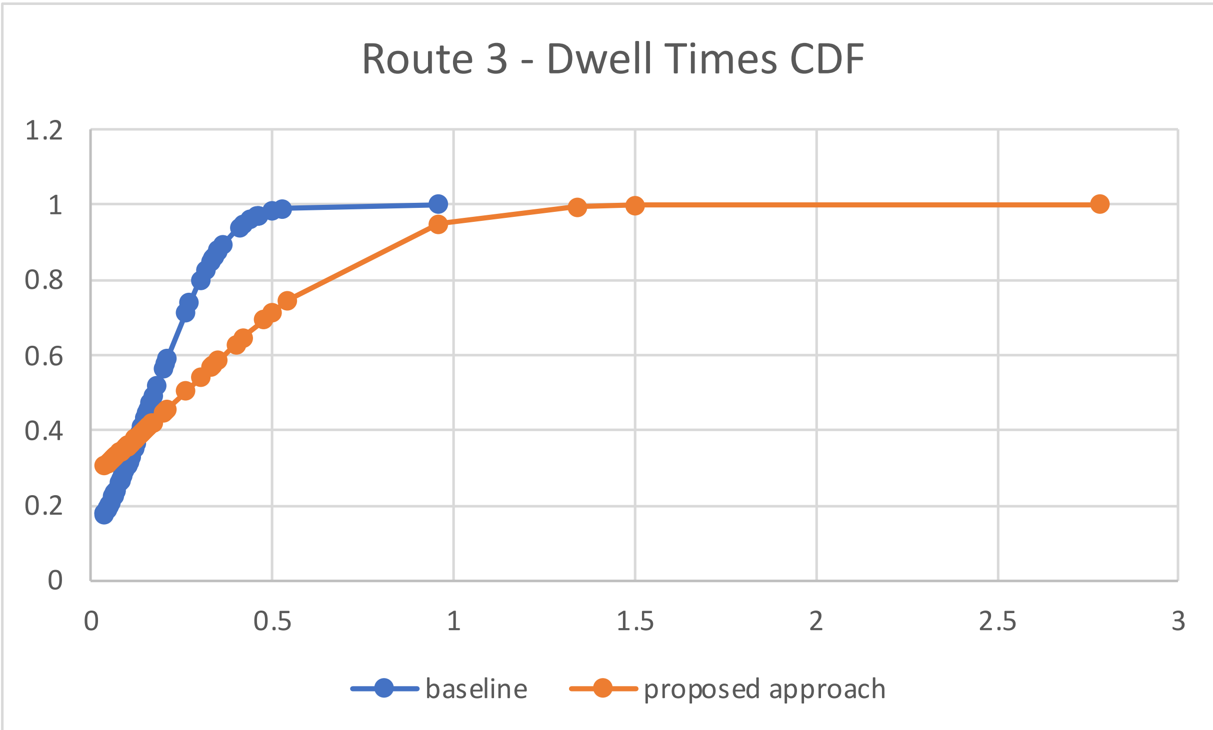

Fig 9: Route 4 Dwell Times CDF

The overall average dwell times are shown in fig. 10. We find that the average dwell time for route 1 increases from 0.1417 to 0.1872 minutes giving a 32.11% increase. For route 2 it goes from 0.1449 to 0.1807 minutes giving a 24.70% increase. For route 3, we have a 46.67% increase in the average dwell time, going from 0.1746 to 0.2561 minutes.

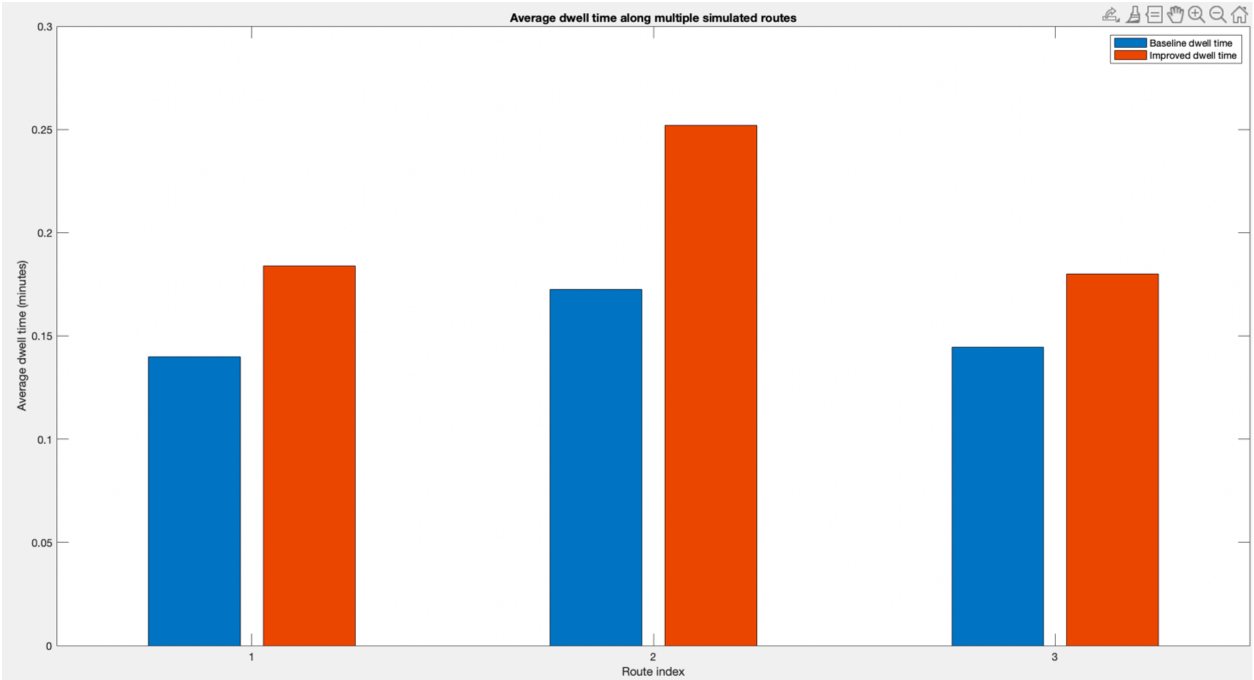

Fig. 10: Dwell times comparison–baseline vs. proposed approach

The number of handovers is calculated as follows:

$$\text{Number Of Handovers} = \frac{N_1 * t_1 + N_2 * t_2 + N_3 * t_3}{t_1 + t_2 + t_3} \tag{7}$$

The number of handovers decreases for all three routes. For the first route, it goes from 74 to 56 giving a 24.32% improvement. For the second route, 348 to 279 giving a 19.82% decrease in the number of handovers. For the third route, we have a 31.82% decrease, going from 88 handovers to 60 handovers in the proposed algorithm.

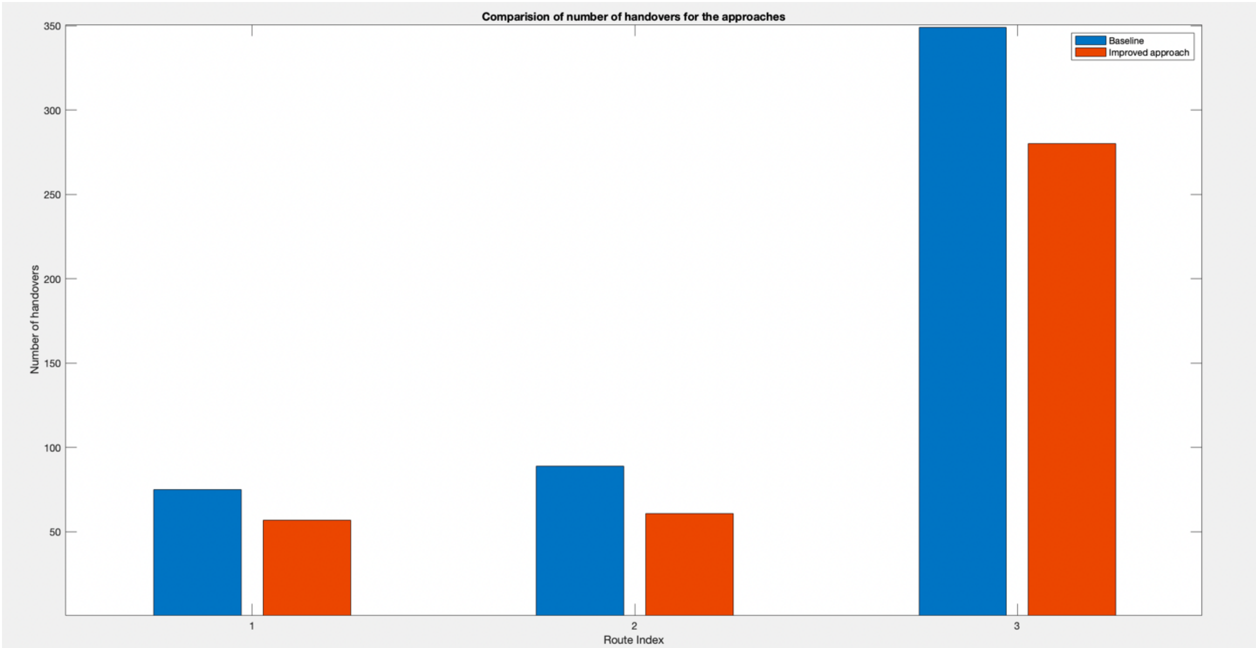

Fig. 11: Handover comparison–baseline vs. proposed approach

The average number of handovers is calculated by taking the weighted average of the handovers across routes. Handovers for baseline versus proposed approach for 3 routes is shown in fig. 11. We can see the decrease in the number of handovers in the proposed approach as compared to the baseline algorithm. Table 1 shows the improvement in dwell times for the proposed approach as compared to the baseline algorithm for all three routes. Table 2 shows the improvement in the number of handovers. It is observed that the ping-pong effect that occurs multiple times in the baseline approach is reduced significantly in the proposed algorithm. The difference is shown in table 4. The overhead of the connection and teardown phases when the ping-pong movement takes place is reduced in the case of the proposed algorithm.

	Average Dwell Times (In minutes		
Route Number	1	2	3
Average Dwell time - Baseline	0.1417	0.1449	0.1746
Average Dwell Time - Improved	0.1872	0.1807	0.2561
Difference	0.0455	0.0358	0.0815
Percentage Increase	32.11%	24.70%	46.67%

Table 1 : Average dwell times comparison across routes

	Number of Handovers		
Route Number	1	2	3
Number of Handovers - Baseline	74	348	88
Number of Handovers - Improved	56	279	60
Difference	18	69	28
Percentage Decrease	24.32%	19.82%	31.82%

Table 2: Number of handovers comparison across routes

Table 3 provides the weighted average over all three routes.

Weighted Average (Over all routes) improvement	
Dwell time improvement (in minutes)	Number of Handovers
0.04623	54

Table 3 : Weighted average improvement – dwell times and handovers

Reduction in ping-pong effect (approx.)		
Route 1	Route 2	Route 3
17 times	65 times	28 times

Table 4: Reduction in ping-pong effect

VI. CONCLUSION

This research gives an optimized algorithm to reduce the frequency of handovers and to improve dwell times in 5G-V2X networks. The simulation is modeled after vehicular networks in an area in LA near Beverly hills. We simulate buildings and model the path loss considering obstacles, distance and other real-world factors. The proposed approach consists of two phases. In the first phase, we predict the destination of the vehicle based on parameters like the current location, the speed of the vehicle and time of the day. The second phase uses this information to construct a trajectory of the vehicle and select base stations that are optimal based on the distance from the trajectory. The baseline approach uses RSRQ values to make the handover decision. We see a significant improvement in the number of handovers as well as the average dwell time in the proposed approach as compared to the baseline.

VII. FUTURE WORK

This research provides a good proof-of-concept of how the proposed algorithm could work when dealing with 5G-V2X networks. There are many ways to extend this research and provide better improvements.

- One way is to use more variables in the distance function used for base station selection. In this case the loads at each base station are hard-coded in the simulation. In real-world scenarios, these are dynamic values that could vary depending on the time of the day, holidays, traffic distributions etc. Modelling this realistically could help study the impact of load on platoon handovers and bandwidth considerations.
- SUMO as well as NS3 provides a rich feature set to simulate mmwave and lte vertical, as well as horizontal handovers. Heterogenous network infrastructure can be modelled. The algorithm can be tested on different models this way.
- The simulation can be run on more routes. And the prediction model can be trained using a real-world dataset and localized to get better route predictions based on historical data.
- The parameters can be fine-tuned to construct a distance function that has all the parameters required to get accurate state information about the environment and reduce the number of handovers and improve dwell time while maintaining continuous connectivity.

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