

AI Enabled Resource Allocation in Future Mobile Networks

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Abstract—The recent past has advocated immense flexibility in the control and elasticity in the resources of the mobile networks. The emerging application domains including autonomous driving, eHealth, smart grid, etc. position the need for the right communication stretch at a pivotal level. It goes without saying that the network operators will experience the dynamic demands like never before owing to an extremely dynamic device layer i.e., IoT. An obvious consequence of this is the uncertainty in the demand estimation and capacity planning of the communication infrastructure. This paper studies the concept of dynamic demand estimation using AI approaches. We start with learning over the mobility and activity patterns of a single user and evaluate the performance of different machine learning (ML) approaches, for example, classification, regression, and clustering. We then move on to more realistic settings, where the learning is carried out for population and autonomous driving. To do so, we use the data-set from Ernst-Reuter-Platz collected as part a Berlin City project that made the data openly available.

Index Terms—Autonomous Driving, Artificial Intelligence, Mobility and Activity Management and Machine Learning.

I. INTRODUCTION

Mobile networks have been playing a key role in evolving cities aiming at transiting to the smart spaces, smart building, smart roads, eHealth, and autonomous driving. Ambitious targets set by 3GPP for 5G advocated its importance for the envisioned digitized era. Pre-5G technologies may mainly be categorized under the Internet-of-People (IoP), whereas 5G is for what we know as Internet-of-Things (IoT). 5G finds its application in different domains including: healthcare, autonomous driving, industry, infotainment, smart homes, etc. Enabling the autonomous driving, 5G is positioned as the key technology to help achieve the envisioned goals of traffic safety, reduction in emission (i.e., 40-90%) and travel time (i.e., by 40%), etc.

It goes without saying that demand estimation for pre-5G technologies have remained a somewhat limited exercise owing to its relatively limited application domains. So as to convey the bulk of information going up to 100 Gbps/km² with high versatility, the devices layer entities of future will require reliable, bandwidth supportive, and ubiquitous communication bit-pipes [1], [2].

A number of research publications have looked into the exploitation of 5G features, mobility, activity, flexibility, and elasticity as well as the bandwidth demand estimation. [3] contributes with a novel technique for handover advancement in a 5G cell system utilizing reinforcement learning (RL). Authors proposed to control the handovers between base-cells utilizing an incorporated RL agent. The agent handles radio estimation reports from the (User Entity) UEs and picks proper handover activities as per the RL structure to boost a long-term utility.

The authors also claim that the handover mechanism can be treated as a relevant multi-armed bandit issue. They analyze the performance of the proposed techniques by utilizing diverse propagation conditions. Similarly, the authors in [4] model the user demand using local and global Markov processes. An RL framework is used to find the ideal resource reservation approach when change probabilities are unknown.

The article [5] uses a well-known supervised learning technique to forecast the evolution of network conditions and, in turn, to improve network performance. The authors have identified prediction and optimization tools, which are then adopted by them and linked them with objectives and constraints of the typical applications and scenarios. The authors also considered making anticipatory networking part of next-generation networks. A deep learning technique is introduced in [6] to maximize the user experience. The authors have well described the essential background and state-of-the-art in deep learning techniques with potential applications to networking. The article gives a very good insight into exploiting deep learning approaches for modeling user satisfaction.

Inspired by the typical handover processes that involve measurement of transmit power threshold values, in another article [7], authors describe the handover method for 5G. This is to say that if a user leaves the coverage area of a cell and enters the coverage area of the neighboring cell, then the signal both cell values are analyzed and the cell with the stronger signal is joined. The future of 5G network slicing and the need for automation of network functions when it comes to design, construction, deployment, operation, control and management of network slices, is detailed in [8]. The authors explained AI procedures for the automation of network functions. Their article also examines the status of AI and ML related exercises being advanced in standards improvement associations and mechanical discussions.

Authors in [9] enhance the Quality of Service (QoS) using RL. The main contribution of the article is an innovative scheduling system, which chooses diverse planning guidelines as per instantaneous scheduler states to limit the parcel delays and bundle drop rates for strict QoS prerequisites applications. In order to manage ongoing scheduling, the RL standards are utilized to outline planning principles to each state and to realize when to apply each. Also, neural networks are utilized as capacity guesses to adapt to the RL unpredictability and enormous portrayals of the scheduler state space.

In another article [10], authors worked with the multifaceted nature of the ideal traffic mindfulness in 5G cloud radio access network (C-RAN) and designed a system for traffic-aware energy optimization. The virtual base cell cluster (VBSC) of C-RAN exploits an information-theoretic way to deal with the model

and break down the uncertainty of cell traffic, caught by remote radio heads (RRH). In a similar work, [11], the authors looked into an SDN empowered 5G VANET to counter the high unpredictability of 5G HetNets. The proposed approach adaptively groups neighboring vehicles as indicated by real-time road conditions utilizing SDN's worldwide data assembling and system control capacities. With the proposed double bunch head plan and dynamic beamforming coverage, both trunks connect correspondence quality, and system heartiness of vehicle groups were fundamentally upgraded.

The discussion so far advocates that there is a large amount of research literature contributing to the improvement of handovers. However, our work targets the handover problem from a slightly different perspective. We address the issue of handovers in the envisioned semi-autonomous driving paradigm, where the vehicles will either be connected and/or autonomously driven. We make use of ML to learn over the activity and mobility patterns of the device layer entities. Having learned on the mobility and activity patterns of the mobile users, the network operations may be made proactively rather than keeping them reactive. This will improve different key performance indicators (KPIs) including bandwidth/resource allocation, QoS minimizing the delays, etc. Moreover, our digital twin(the digitized road of Ernst Reuter Platz Berlin) tells us how this can be beneficial for the operator and customer point of view. Recourse Allocation and different machine learning approaches are helping us in allocating different types of resources. Hence, we are not working with any type of simulation. We are working with a real dataset provided by the Berlin city government [12] and the University of Cork, Ireland, [13] to produce real-time results with minimal assumptions.

II. DOMAIN SETTINGS AND DATA-SET ANALYSIS

To validate the contribution of this paper (i.e., the demand estimation and resource allocation approaches), we consider two settings: single-user settings and population settings. For the former, we learn over the mobility and activity patterns of a single user, whereas later learns over the mobility of a bigger population (mainly inspired by the autonomous driving). It is worth highlighting here that the motivation to work with the two settings comes from different sources. We found 4G traces for different user's mobility like static, pedestrian, car and train [13]. Lastly, the dataset we used was acquired by Ernst Reuter Platz Berlin, Which consists of traffic Density at different cells at that place [12].

A. Single User Settings

For this setting, we relied on a study conducted by University College Cork Ireland [14], which provides a 4G trace dataset composed of client-side cellular KPIs collected from two major Irish mobile operators. The dataset captures different modes of mobility including static, pedestrian, car, tram and train. The 4G trace dataset consists of 135 traces, with an average duration of fifteen minutes per trace, with visible throughput ranging from 0 to 173 Mbit/s at a granularity of one sample per second. The traces are generated from a renowned non-rooted Android network monitoring app called G-Net Track Pro. This app allows us to gather various channel related KPIs, context-related metrics, downlink and uplink throughput, and cell-related information. This dataset is only used for the single user at a time.

Dataset Analysis: We now provide the analysis of datasets for this setting. On the base of single user mobility pattern, which is based on different types of features like: timestamp, longitude, latitude and speed etc. Each user (i.e., in: bus, car, stationary and train, etc.) has varying communication demands. 15-minute dataset with one-second data resolution provide adequate information to conceive the near future communication demands of the users. Each user has different feature values, which gives us the proper evidence that this data is not fake as show in the Figure 1.

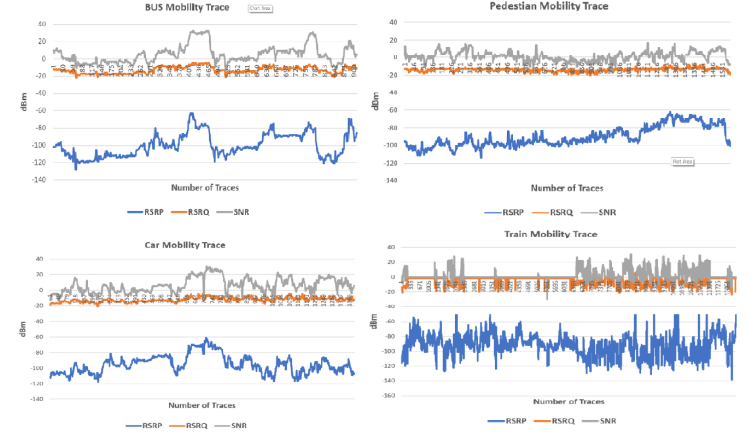


Fig. 1. 4 Entities 15 Minutes Traces

We took one profile with three features (SNR, RSRP and RSRQ) from each user to analyze the pattern. We can see that train data-set have more variance than other because of the speed.

B. Population Settings

A project dealing with the processing of traffic flow and parking lot data. These data are collected via an IoT middleware capturing the data from many traffic analysis sensors, parking sensors, activity analysis sensors, etc. deployed around the Ernst-Reuter-Platz, Berlin, Germany. After the anonymization of the data, they are used by the DAI Laboratory to develop various applications. There are basically two types of data available. On the one hand, data some from the so-called “flow monitoring” and on the other hand, the data comes from the so-called “parking space monitoring.” But we are focusing here on *traffic density*. So far, 8 months of data have been collected near and around the TU Berlin. The deployed sensors on the test-road in Berlin capture different types of vehicles (e.g., motorcycle, car, truck, etc.) Obviously, different vehicle types have varying communication bit-pipe requirements for C-V2X (cellular vehicle-to-everything) communication and infotainment. Thereby, different variations in traffic intensity of different vehicle types will require dynamic communication capacity with associated QoS parameters (e.g., end-to-end latency, throughput, reliability, etc.). Analyses of such a dataset allow us to estimate the dynamic demands of envisioned mixed traffic (i.e., traditional, connected, and automated vehicles, etc.). Hence, smartly chosen assumptions for communication bit-pipe requirements for different applications (e.g., ITS services, infotainment, etc.), we are able to predict the communication requirements and consequently assist in capacity planning on different road segments.

For ready reference, in Figure 2, we show the sensors deployment. In the figure, red dots show the sensor positions to cover the

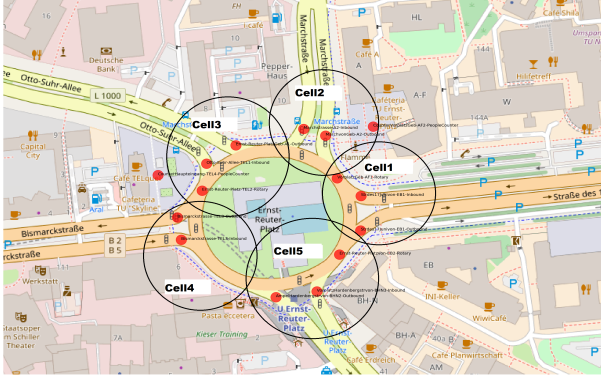


Fig. 2. Figure depicting sensors deployment and communication coverage footprints at Ernst-Reuter-Platz, Berlin

renowned roundabout of Berlin, Ernst-Reuter-Platz. Five sensors deployed at different locations count outbound traffic. Eight sensors collect the inbound data with two outer bound sensors.

We now give a quick overview of the sensor deployment and coverage footprint at Ernst-Reuter-Platz. It should be noted that the coverage footprint is a visual representation of how different sensors (consequently the vehicles) are connected to the data-center in our lab. situated in TEL-building next to Ernst-Reuter-Platz. For the ease of understanding, we term each coverage footprint as a cell. Cell-one covers sensor nos. 8, 11 and 7, whereas cell-two covers sensor nos. 9 and 12. Cell-three covers sensor no. 3, 5, and 10, Cell-four covers sensor nos. 4 and 6, and finally, Cell-five covers sensor nos. 1, 2 and 13.

Dataset Analysis We see some drawbacks in a single-user setting dataset e.g., we are unable to tell the traffic density at a certain points. This is because of the reasons: i) data consists of only 15 minutes and sometimes it starts from the morning and sometimes from noon; ii) We do not have continuous behavior; iii) Locations are different for all users. Hence, we looked for a more suitable dataset with required features. Having acquired the right dataset, we needed to verify the ground truth of the dataset. Figure 3 shows the first two Monday’s dataset and pattern in this graph correlate with each other means data is in the right shape. Regardless of data, we have some concern, We have carried out a complete exploratory data analysis to understand traffic density patterns in Ernst-Reuter-Platz roundabout. It also aims to assess the quality of the different data sources in order to be used as data input for predictive modeling of traffic in the roundabout. Therefore, the main resources will be traffic, although it will be explored if the other sources can be useful to extract insights about traffic behavior. Finally, it is important to note that some of the days and sensors with data, do not have readings for every hour. Although not every day has the same number of rows, it seems realistic to consider that a day is complete if it has roughly 54,000 sensor readings. In the table above there are some days with a number of readings significantly below 54,000 and that means some sensors and or hours do not have data. For instance, there is no data from 03:00am 2018-01-18 till 11 : 00am 2018 – 01 – 19. It is not clear how vehicle count/speed is measured. The information obtained, states that: the analysis software tracks objects it detects as cars. In the live video feed, we define two boxes, source and destination. If the object passes

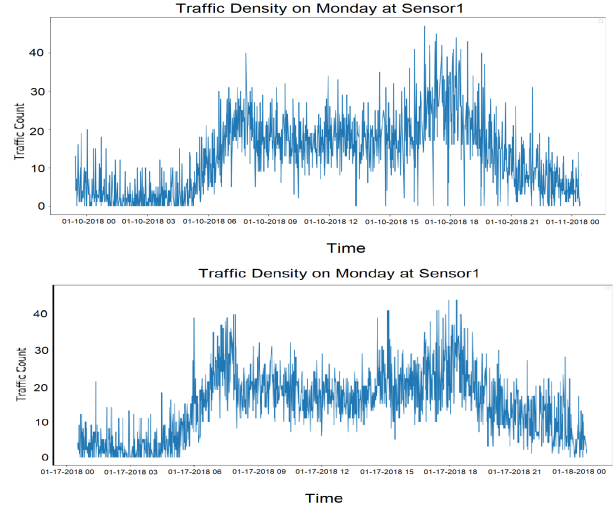


Fig. 3. 2 Monday’s Traffic Count

through the source and then through the destination box, it counts as +1. So the number in the data indicates the total number of detected vehicles that passed through the defined boxes. The former definition implies that it will count only moving vehicles.

Furthermore, it should also be highlighted that count types are missing missing at times. This is to say that not every measurement point provides all vehicle types (e.g., some provide just cars) and that cells providing types like trucks or motorcycles do not always provide records for all types. Despite this issue, one would expect that the Overall type is always present, however, in a few registers, it is not. For instance, in a set there are nearly 200 minutes with just Truck data.

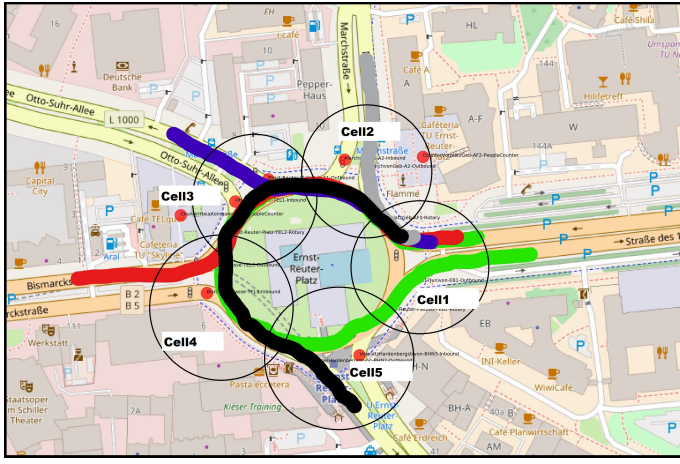
III. AI-ENABLED DEMAND ESTIMATION (AIDE)

Consider Figure 4, which depicts our understanding of the traffic flow on the considered roundabout (i.e., Ernst-Reuter-Platz, Berlin). As can be seen that we have created 5 paths (the path with entry to and exit from roundabout), differentiated by colors i.e., grey, blue, red, black, and green. It goes without saying that each path is covered by different cell coverage footprints, which we decompose the paths in multiple trajectories to show the entry and leaving path segments with respect to cells. This is summarized in Table I.

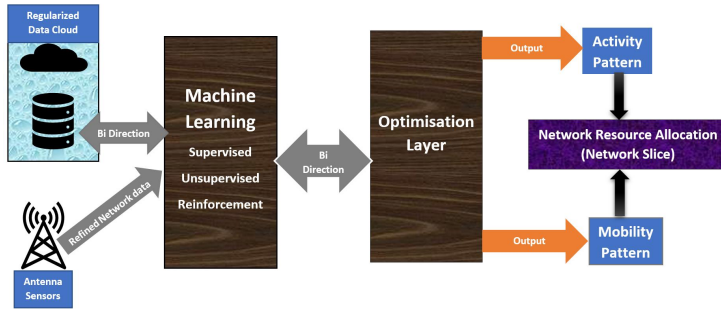
TABLE I
TRAJECTORIES (REPRESENTED BY TRA.)

		Outbound				
		Cell 1	Cell 2	Cell 3	Cell 4	Cell 5
Inbound	Cell1	Tra.1	Tra.2	Tra.3	Tra.4	Tra.5
	Cell2	Tra.6	Tra.7	Tra.8	Tra.9	Tra.10
	Cell3	Tra.11	Tra.12	Tra.13	Tra.14	Tra.15
	Cell4	Tra.16	Tra.17	Tra.18	Tra.19	Tra.20
	Cell5	Tra.21	Tra.22	Tra.23	Tra.24	Tra.25

Having defined the trajectories, we have worked out a basic design model containing different stages. The main idea is to track the mobility and activity of the user to perform different operations like network slicing. We have a data server which contains the regularized dataset to perform supervised and unsupervised techniques. Basically, data comes from the real-time data network and then it is processed with different machine



learning algorithms to trace the mobility and activity of the user. The process can be seen in Figure 5. Below we explain our



technique: Data preprocessing consists of data regularization and data personalization. Data regularization means finding the best values for missing data and refining the data. Data personalization means adjusting the data for different purposes. Data representa-

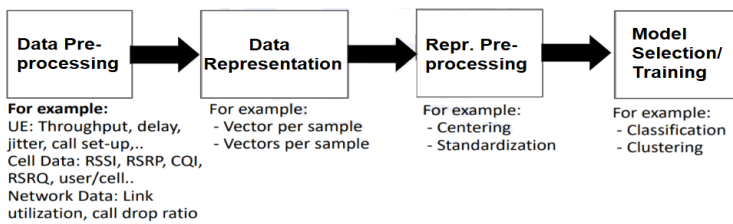


Fig. 6. Processing Model

tion helps separate the features of the dataset, so we perform different operations such as k-fold validation. Standardization may be needed for improving the result and then we will choose the best algorithm for the dataset. This is the main process that can be used for different machine learning techniques.

IV. COMMUNICATION RESOURCE ALLOCATION FOR ENVISIONED MIXED TRAFFIC

Now that we are able to estimate the dynamic communication bit-pipe demands on very granule levels for specific road segments (refer to Section III), we implement various algorithms for

allocating communication resources against demands. The results are pretty good with classification. But the given fact that it can be improved by performing data regularization and parameter tuning. Root Means Squared Error (RMSE) is the validation metrics to measure the performance of given machine learning algorithms.

A. Single User Setting Results

Given the dataset is limited to more or less 15-minute duration for each vehicle. This time period is not enough to provide a better predictive solution. It means that we need more data about all vehicles. However, we can see the algorithm result over this time period in Table II.

TABLE II
SINGLE USER SETTING RESULTS

No#	Approach	Algorithm	RMSE
1	Regression	SVR	10.43
2		KNR	6.37
3	Classification	Ada Boost	5.99
4		Decision Tree	4.72
5		GaussianNB	9.06
6		KNN	10.60
7		Random Forest	8.89
8		SVM	6.38
9	Clustering	Affinity Propagation	288.68
10		Agglomerative	99.18
11		K Mean	163.34
12		Mean Shift	218.17

Based on the movement of a vehicle, our software can predict the next location, the signal strength and can assign the right amount of bandwidth resources according to customer subscription. Since this is a single-user story, the predictive solution only infers about one vehicle at a typical time-stamp.

B. Population Settings Results and Resource Allocation Algorithms

In this section, we focus on resource allocation for the population of vehicles passing through specific road segments. Time-series dataset results are pretty impressive with classification algorithms even in k fold validation. Please refer to Table III.

TABLE III
POPULATION SETTING RESULTS

No#	Approach	Algorithm	RMSE
1	Regression	SVR	9.09
2		KNR	9.81
3	Classification	Ada Boost	7.41
4		Decision Tree	0.0
5		GaussianNB	1.92
6		KNN	10.74
7		Random Forest	9.21
8		SVM	9.07
9	Clustering	Affinity Propagation	7.03
10		Agglomerative	18.08
11		K Mean	27.67
12		Mean Shift	14.85

An important fact to highlight here is that inspired by the user-centric paradigm, we have taken great care of satisfying device layer demands and at the same time maximizing the profit function of operators i.e., by modeling the profit function of the operator as a function of users'/ vehicles' satisfaction. The details are avoided here due to space limitations, however, the readers are encouraged to refer to a variant of our approach in [15] [16].

C. Resource Allocation Models

1) *Over-provisioning*: Over-provisioning in our context means that the operator needs to provide the resources equivalent to the highest demand peak at a certain place and at a certain time. Obviously, this will leave the operators with excessive unused communication resources for a major part of the day.

2) *Proportional Resource Allocation*: This model deals with an equal division of resources amongst all cells around the Ernst-Reuter-Platz. If the sum of all the cell bandwidth is less than or equal to the required bandwidth than this algorithm just assigns the bandwidth as required by the specific cell. Else it calculates the percentage of each cell from the demand and then takes this percentage of each cell and calculates the percentage from available/fixed bandwidth and then it assigns to each cell. The given table describes the calculation of this algorithm if the demand increases from fixed bandwidth. In Figure 7 one

TABLE IV
PROPORTIONAL RESOURCE ALLOCATION

	Available/Fixed bandwidth		Demand	
Total	150	100%	200	100%
	Bandwidth	Percentage	Bandwidth	Percentage
cell1	60	40%	80	40%
cell2	45	30%	60	30%
cell3	15	10%	20	10%
cell4	7.5	5%	10	5%
cell5	22.5	15%	30	15%

can see that we took 10 minutes to see how the algorithm performs. There are five cells with different values. Algorithms perform according to our expectation and if the values are greater than fixed resources than it will perform the above mentioned procedure.

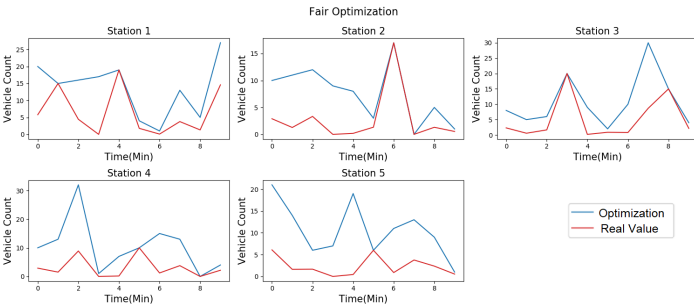


Fig. 7. Proportional Resource Allocation

Vehicles' profit function will be maximized if the bandwidth is less than or equal to the fixed/available bandwidth, whereas operators will also increase their satisfied resource consumer pool. However, if the demand increase over time than demands of sub-set of vehicles will not be met due to lack of available resource. In this case, the operator will get negative feedback that will cause churning.

3) *Priority based Resource Allocation*: This algorithm is based on the maximum traffic of two cells. This algorithm helps us either if the sum of two cells demands is less than or equal to the available demand or any cell's bandwidth is less than or equal to the available demand. Let's take an example if the sum of demanded bandwidth is less than or equal to the available demand than it returns as it is bandwidth demand to each cell.

If the demand increases then it takes a first larger number and see if the bandwidth demand is less than available demand then it assigns the bandwidth as it required and remaining bandwidth calculated of the base of the percentage of each remaining cell with respect to the demand. If an algorithm finds that the two largest numbers from cells where the large volume of bandwidth required. If the sum of both cells bandwidth demand is less than or equal to available demand then it will assign the bandwidth as they required and remaining bandwidth calculated of the base of percentage of each remaining cell with respect to the demand. Else the given algorithms perform as the Fair Resource Allocation algorithm is performing above. This seems to be one of the

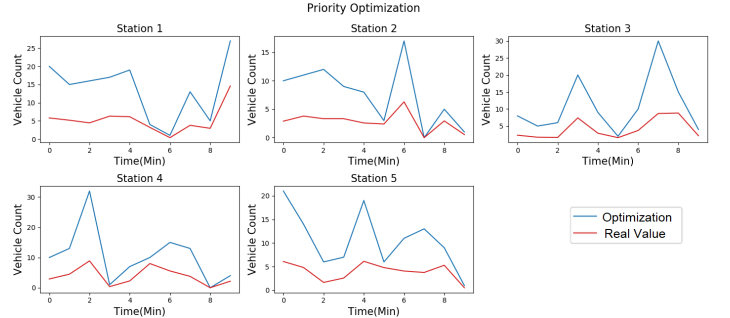


Fig. 8. Priority based resource allocation

effective ways to provide the bandwidth where traffic congestion becomes a normal phenomenon. This algorithm gives priority to the max traffic either two-node or one node. Autonomous driving needs bandwidth therefore this method will help us to deal with the different driving situations as well. However, other cells will get low bandwidth and the operator may get negative feedback from the users.

4) *Uniform Recourse Allocation*: The idea behind uniform recourse allocation is to ensure the vehicles receive the required bandwidth with proper QoS requirements. Operators deploy the resources following the demands of the vehicles, which is implementable by enabling technologies like Virtualized Network Functions and Software-Defined Networking. This means that if the user's demand increases then the number of resources will also increase.

5) *Manual Recourse Allocation*: This method is more on the operator side. The operator can manually select the bandwidth for a specific cell for certain periods of time. There are two options in this algorithm: one operator can assign the bandwidth by percentage, the second operator can give the quantity of bandwidth each cell manually. Figure 8 expresses the manual technique that we did, bandwidth value is not changing because this value will be the same for certain periods of time.

D. Results

We have seen the detail description of data in previous sections. For the experiments, we use sensor 1, named "AmpelHardenbergstrvon-BHN2-Outbound" owing to the fact that analysis of other data will be similar.

E. Bandwidth Demand Estimation

As we have seen in the performance of different algorithms which provide the traffic count at certain points and a certain place. These algorithms help us to ensure that they provide the best results with high precision of accuracy.

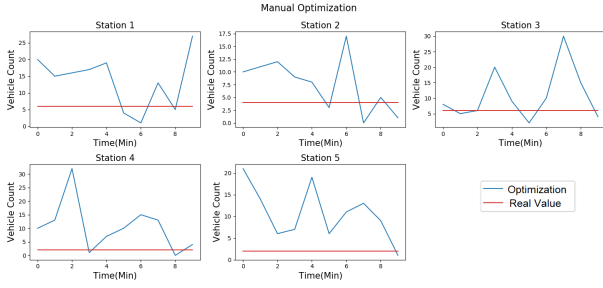


Fig. 9. Manual Recourse Allocation

We can scale up or scale down according to the customer's variances because we don't have the dataset for the Activity pattern of any kind of user. For easy to understand the behavior we assume that one vehicle needs one Mb/s bandwidth at any time if the vehicle enters within the range of the sensor. on the base of this assumption please refer to a comparison in the following section.

1) *Resource Allocation Models - A Comparison:* We have selected randomly one hour from dataset and try to calculate the overall cost at all cells and then we fix the resource with different time resolutions e.g., per hour cost, half hour cost, 15 minute cost or per minute cost. Moreover, we calculate the result only operator based we can add profit margin of operator and other cost. For this comparison, we have modeled a realistic profit function inspired by our earlier work (please refer to [16])

In what follows next, we provide brief conclusions based on our analysis for different resource allocation models.

2) *Over Provisioning:* The traditional way of solving the problem is that we have a fixed number of resources on each cell but since we have 5G this has an impact on our idea very efficiently. Now we can dynamically manage the resources.

3) *Proportional Recourse Allocation :* Table V shows that the beneficial way would be to chose per minute recourse allocation because it has least cost over other resolutions. Second best is per 15 minute cost. Cost increases with increase in time duration.

TABLE V
FAIR RECOURSE ALLOCATION COST ANALYSIS

	Per Hour Cost	Half Hour Cost	15 Mint Cost	Per Mint Cost
cell1	900	858	732.29	259.76
cell2	766.26	738.68	707.26	248.34
cell3	976.74	753.07	570.18	184.052
cell4	900	765	697.65	234.98
cell5	727.86	700.51	648.47	240.85
All cells	4270.87	3815.28	3355.86	1168.0

4) *Priority based Recourse Allocation :* This algorithm performs less good than a fair recourse allocation algorithm according to the cost. Table VI represent the result of different time resolution. Same thing here Cost will increase by increment in the time duration.

5) *Uniform Recourse Allocation :* In uniform Recourse Allocation operators provide the network resource as needed at that time so cost always depends on a number of users at that time.

V. CONCLUSION

From the Cork University 4G LTE Dataset, we were able to proactively predict the user's mobility, unlike the previous

TABLE VI
PRIORITY RECOURSE ALLOCATION COST ANALYSIS

	Per Hour Cost	Half Hour Cost	15 Mint Cost	Per Mint Cost
cell1	1140	1140	868.68	270
cell2	1140	1080	950.27	249.14
cell3	1200	1088.37	737.83	176.55
cell4	1200	915	847.5	232.33
cell5	1200	1110	991.96	239.95
All cells	5880	5333.37	4396.25	1168.0

reactive mechanisms of network operators. This ensured timely communication and required throughput for different applications. The problem was solved using machine learning algorithms (Random Forest, Ada Boost, etc.). The provided solution helped us to ensure optimal network slice-based on traffic prediction at a specific time and location. By looking at results, we can infer that the cost is always dependent on the time resolution set by the operator in the resource allocation algorithm. These algorithms were properly assessed by Real Dataset not over any Simulation. The proposed solution in the form of different algorithms is based on different situations. Priority recourse allocation algorithm proved to be the best solution of mixed traffic environment.

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