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THE FIRST PYTHON-BASED SIMULATOR : SYNTHETIC NET

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ABSTRACT— Increasing use of mobile networks requires research into new features in order to provide better and better services leading to the development of 2G, 3G, 4G and 5G now and developing and deploying these services requires more complex and costly infrastructure and to overcome this problem the author of this paper. build a new 3GPP-based template (machine learning artificial Intelligence (AI) algorithms) that can mimic 5G and other mobile services. The 3rd Generation Partnership Project (3GPP) brings together seven communication development organizations (ARIB, ATIS, CCSA, ETSI, TSDSI, TTA, TTC), known as "Partner Partnerships" "and provides its members with a stable environment for the production of Reports and Data which explains 3GPP technology.

Therefore, the rapid emergence of mobile system design in 5G and above raises the need for research into new features, design proposals and solutions in the practical settings of various deployments and operating cases.

KEYWORDS— Cellular networks, 3GPP, Machine learning Artificial Intelligence algorithms, Organizational Partners, 5G

I. INTRODUCTION

Although many 4G and 5G system templates are available today, there is a great need for a complete and realistic 3GPP compliant system template that can support the testing of a wide range of automated AI network solutions proposed in the literature. In this paper we present such a template built into AI4networks Lab, called SyntheticNET. It is the first python-based template that fully complies with 3GPP 5G 15 standard releases and can be upgraded for future releases.

After all online, electronic domination, e-commerce, health and ubiquitous use of infotainment,

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complete design and functionality of emerging mobile networks is one of the best in the emerging digital community. Local tests offer very sensible tests. for a new network design, solution or feature. However, relying on the field test alone to evaluate all proposed projects, solutions or feature is not possible due to the cost, time and effort required to run the field tests. For this reason, only the most promising projects can be suitable for investment and resources needed in field trials. Additionally, in view of significant investment and risk participation, mobile operators seek to reduce the likelihood of significant damage to the live mobile network operational even during the pilot phase. For 5G networks, given the increased complexity, the process of designing a complete network configuration that can maximize all Key Performance Indicators (KPIs) such as coverage, capacity, storage and energy efficiency is an even more challenging task. Identifying and maintaining.
Proper network configuration is required for network operators to deliver on the promises of highly anticipated 5G networks. A new 5G network is being developed and new network functionality and solutions are being developed for the effective development of 5G and beyond, especially automated AI network solutions as suggested in this paper. , in the real world without previous testing, would be an expensive process and could not be done literally. To solve this problem, system-level simulators are widely used in both industries and disciplines. All available simulations support 5G simulation but do not have AI support that can be used to predict mobile user movement and based on AI navigation helps select the nearest Base Station which can reduce power consumption and increase the quality of mobile service. SyntheticNET template is flexible, very small, multi-functional and built to comply with 3GPP 15 Release [10]. The template presented supports a large number of different features such as dynamic calculations, the actual HO condition and a computer-assisted future computer to name a few. Instead of Objected-Oriented Programming (OOP)-based architecture as existing templates, SyntheticNET template supports commonly used web files (such as SQL, Microsoft Access, Microsoft Excel). Site information and user information, configuration parameters, antenna pattern etc. can be imported directly into the template. As a result, the simulation space is very real and close to the actual distribution conditions. The Python-based platform and the flexibility of different input and output data formats in the SyntheticNET model allows for authentication of features related to Self Organizing Networks (SON) and new AI-based network solutions [7]. Mobile operators can use it to edit, test or upgrade 5G networks. The research community can also benefit from this by using new ideas in the standard 5G system model based on 3GPP.
The main distinguishing features of SyntheticNET compared to existing simulations include: modular structure to facilitate counter-validation and future release development, a flexible distribution model using measurement-based measurement, ray-based tracking or AI-based distribution model, the ability to import a data-based data sheet based on the actual characteristics of the vendor channel such as the antenna and power consumption pattern,5G flexible statistical support, real-time user-defined navigation patterns found on real-world location maps; implementation of the information provision (HO) process, and installation of a computer based database. Another important feature of SyntheticNET is easy to use to test

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automated AI network solutions. Being the first 5G-based python template, this is easily, in part due to SyntheticNET's built-in ability to process and analyze large data sets and integrated access to machine learning libraries. Therefore, SyntheticNET simulator provides a powerful educational platform and industry alike to explore not only new solutions for designing, deploying and deploying existing and emerging mobile networks but also enabling AI to be empowered for deeper automation in the future.

II. RELATED WORK

Characterizing Coverage and Downlink Throughput of Cloud Empowered HetNets

In this paper, we introduce the concept of various cloud-powered networks. We suggest a simple but effective linking method for the selection of remote radio head (RRH) for the desired mobile user (MU). We introduce the concept of user interaction that enhances user performance by contributing to a number of areas.

Predictive and Core-Network Efficient RRC Signalling for Active State Handover in RANs With Control/Data Separation

Frequent allocations (HOs) in the case of dense small cell delivery systems can lead to a dramatic increase in signature overhead. This raises the paradigm flexibility to a smart cellular design with intelligent navigation management. In this case, a future radio access network with logical differences between control aircraft and data has been proposed in the research community. It aims to overcome the limitations of conventional structures by providing high-level data services under the integration layer umbrella in dual connection mode.

Coverage, capacity, and energy efficiency analysis in the uplink of mm Wave cellular networks

In stochastic geometry concept, we introduce an analytical framework to test signal-to-interference-noise-ratio (SINR) coverage on high-frequency cellular network networks. Using the distance-based optical opportunity function (LOS) function, the location of LOS and non-LOS users is modeled as two independent processes of a nonhomogeneous Poisson point, each with a different pathoss phenomenon. The analysis considers the individual component power control (FPC), which includes user transfers based on location-based channel conversions.

Energy Efficient Inter-Frequency Small Cell Discovery in Heterogeneous Networks

In this paper, we use stochastic geometry, investigating the average energy efficiency (AEE) of a user terminal (UT) in a network connection over two different phases, where two phases operate on different network frequencies. In such deployments, a typical UT should periodically undergo process small cell acquisition process (ISCD) in order to locate smaller cells in its area and benefit from a higher data rate and the potential for existing small cell traffic traffic. We assume that the base channels for each phase and UTs are randomly located, and we find a moderate ergodic ratio and UT power consumption, which was later used in our AEE experiments.

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Mobility prediction-based autonomous proactive energy saving (AURORA) framework for emerging ultra-dense networks

Increased network power consumption is a major challenge that prevents the transmission of large networks (UDNs). Although a number of energy efficiency (ES) schemes have been proposed recently, these plans have one common lease. Operating in reactive mode, i.e., increasing ES, cells are shut off / CLOSED in response to changes in cell loads. Although, significant benefits of ES have been reported in such ON / OFF systems, the natural redesign of these ES systems reduces their ability to meet the very low delays and high QoS expected from future mobile networks vis-a-vis 5G and beyond of that.

Concurrent Optimization of Coverage, Capacity, and Load Balance in HetNets Through Soft and Hard Cell Association Parameters

Ultradense heterogeneous networks (HetNets) emerge as an inevitable way to deal with power loss on mobile networks. However, the unequal load between small and large cells and the misuse of resources as a result of HetNets remains a long-term problem. This paper addresses this issue by introducing a solution to increase coverage and volume while minimizing load imbalance between large and small cells. The most recent research on the topic focuses on the development of the installation, capacity or load, or a combination of these three interrelated objectives. We construct the development problem as a function of two solid parameters namely the antenna tilt and transmission power, as well as the soft parameter, each cell offset, affecting coverage, capacity, and direct loading. The resulting solution is a combination of conflicting coverage and volume improvement (CCO) and self-adjusting load (LB) functions (SON).

Challenges in 5G: how to empower SON with big data for enabling 5G

While al dente the 5G character is yet to emerge, network congestion, node diversity, control and data flight, network virtualization, heavy and local cache, infrastructure sharing, simultaneous operation on multifrequency bands, timely use one of a different medium. access control and visual layers, as well as flexible spectrum distribution can be considered as some of the potential 5G components. It is not difficult to predict that with such a combination of technology, operational complexity and OPEX can be a major challenge for 5G. To address similar challenges in the context of 3G and 4G networks, more recently, self-service networks, or SONS, have been extensively researched.

Mobility Management in 5G and Beyond: A Survey and Outlook

The powerful increase in mobile traffic from mobile devices highlights the need to make motion management in future networks more efficient and less hassle than before. The Ultra-Dense Cellular Network concept that combines cells of different sizes with normal bands and mmWave is seen as a panacea for outstanding volume reduction. However, movement challenges in a wide range of high density motley networks with high frequency and mm Wave bandcell will be unprecedented due to the multiplicity of delivery conditions, as well as the effect of signal interference and data interference on a variety of devices. Similarly, problems

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such as user tracking and mm Wave cell detection with small beams should be addressed before the outstanding benefits of emerging mobile networks can be achieved. Travel challenges are also highlighted when considering the benefits of 5G multi-Gbps wireless connection, <1ms delays and support for devices traveling at high speeds of 500km / h, to name a few. Apart from your importance, there are few travel surveys that are mostly focused on adhoc networks. This paper is the first to provide a comprehensive survey on the panorama of travel challenges in overcrowded mobile networks.

Spatiotemporal Mobility Prediction in Proactive Self-Organizing Cellular Networks

Travel forecasting, which is one of the key features of allowing self-organizing networks, is aimed at better management of future mobile networks, which are thought to be very dense and complex due to the combination of various technologies. This opens the way for booking resources prior to actual delivery to get a sense of seamless delivery and predict distribution of user traffic. In this book, we have used a semi-Markov model to predict spatiotemporal movements associated with stable condition and to analyze cellular networks. 90% high predictive accuracy is achieved by testing the tests found on real network tracks produced by the smart phone app.

A Machine Learning Based 3D Propagation Model for Intelligent Future Cellular Networks

In modern wireless communication systems, radio broadcasting modeling has always been an important function in system design and performance improvement. These models are used on mobile networks and other radio systems to measure the loss of signal or signal strength received (RSS) to the receiver or to indicate a signal-rejected area. An accurate and rapid rate of road loss is essential to achieve the desired development goals. Modern broadcast models are based on a local scale and are limited in their ability to capture idiosyncrasies of various broadcast locations. To address this problem, ray-tracing-based solutions are used in commercial planning tools, but they are often time-consuming and expensive. In this paper, we propose a Machine-Based Approach (ML) method to align output-based or ray-based models, to create radio wave modeling and RSS ratings. The proposed ML-based model uses a predetermined set of intelligent predictions, including transmission parameters and visual and geometric features of the broadcast area, to measure RSS. These smart predictions are readily available on the network and do not require additional configuration.

III. METHODOLOGY

A CASE STUDY USING SyntheticNET: AI-ASSISTED MOBILITY PREDICTION FOR HetNets

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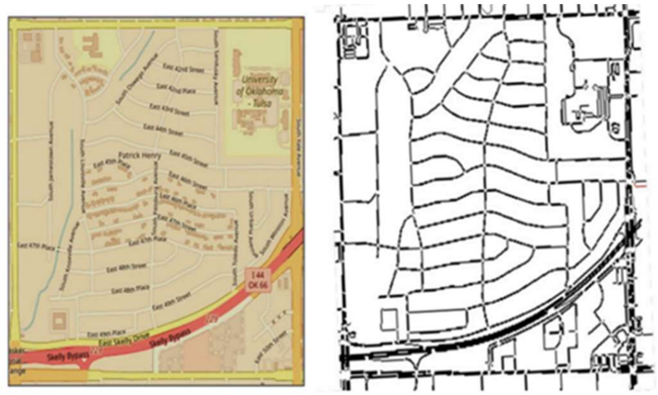

Figure-1 : Realistic road map from SUMO

In this section, we provide one example of the use of SyntheticNET template with an example that is not possible with simulations that do not actually reflect movement patterns and movement management and HO processes on the network. This case study briefly shows how we can achieve AI-enabled traffic forecasts for mobile subscribers

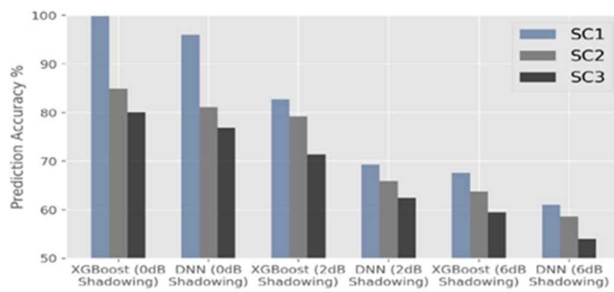

Figure-2: Performance of AI-assisted mobility prediction techniques in HetNets

User Mobility Prediction can be one of the key features of AI-based and next-generation network automation. This could enable booking of network resources to be identified in future cells for seamless HO information and traffic prediction measurement purposes to load and drive SON energy saving activities, as well as to improve battery life.

In the first step, we stop network transmission by entering the site information with the location of several macro and smaller cells, as well as other related parameters (strength, height, slope, azimuth etc.). Then we feed the actual user flow sequence taken from SUMO to SyntheticNET template. To obtain the required user movement data from SUMO, SyntheticNET first transferred the network file and demographic definition file to SUMO. Network file defines the roads and intersections where impersonation vehicles travel during simulation. Population file contains general statistical information that includes the number of homes, housing units, schools and workplaces, the level of free time work, etc. Mobile users automatically travel from home to work and vice versa. However, additional trips when users visit an entertainment venue or grocery store by a defined percentage are also being adjusted. Additional trips are considered to be a representative of the random increase in user trajectories. In addition, the disruption of daily user routes between home and workplace is also remedied.

SUMO then performs simulation of input data from SyntheticNET and generates a real-time navigation pattern for mobile users within a set period of time. Virtual transport routes

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developed by SUMO and used by mobile users in the SyntheticNET simulation module. During trajectory, users perform HO as they move through the cells. SyntheticNET Template also tracks user location and provides cell id to be used as input into AI-enabled solutions for motion prediction purposes.

IV. SIMULATION EXECUTION OVERVIEW

BLOCK DIAGRAM

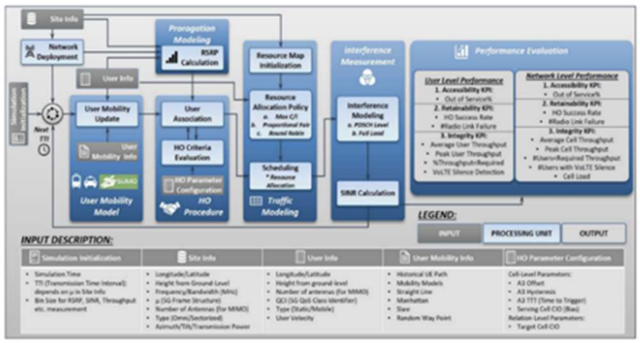

Figure- 3 : SyntheticNET simulator high-level block diagram.

SIMULATOR EXECUTION OVERVIEW

The initial setup of SyntheticNET simulator requires setting up the following items respectively:

• The duration of simulation.

• Transmission Time Interval (TTI) length - which is dependent on the 5G μ parameter.

• Network deployment - BS types, tilt, azimuth, power, scheduling scheme, operating frequency, bandwidth, number of tiers etc.

• Network-level parameter configuration - which may be unique for individual BSs e.g. HO parameters.

• Relation-level parameter configuration - which involves the parameters affecting adjacent BSs on same frequency and different frequency as well.

• UE description - location, static/mobile, height, number of antennas etc.

• UE mobility features - Random waypoint, SLAW Model, Manhattan model, real traces etc.

• UE historical location - to help evaluate AI based advance mobility management for example proactive HO management, load balancing and energy efficiency.

• Database of historical KPIs and parameter value pairs for enabling AI based network automation.

After execution, the SyntheticNET simulator begins processing the data for each of the pre-defined modules. For each TTI, network level KPIs and user information KPIs are calculated. As the simulation progresses, the SyntheticNET template uses HO in a better cell when the HO process is reached. Next, resource allocation takes place based on the selected resource planning system and then the rate of PRB level disruption across all planned UE. When the value of the previous TTI reaches the duration of the simulation, an output file is generated that provides UE level and network KPI levels. In addition, an entry file containing a signal level

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from all nearby BSs and other interested network level statistics is generated. This log file provides additional information that can be used to suggest better solutions to reduce distraction and traffic management.

V. IMPLEMENTATION

Implementation is one of the most important activities in a project phase where one has to be careful because all the efforts made during the project will be very collaborative. Implementation is the most important stage in achieving a successful system and gives users the confidence that the new system is working and running. Each program is evaluated individually during development using sample data and ensures that these systems are connected in the manner specified in the program schedule. The computer system and environment are tested satisfactorily for the user. The application phase has less sophistication than system design. It has a lot to do with user training, and file conversion. It is possible that the system requires extensive user training. The initial system parameters must be changed due to configuration. A simple operating system is provided so that the user can understand the different functions clearly and quickly. Different reports can be found in the inkjet printer or dot matrix, which are available for user use. The proposed system is very easy to use. The term is often used to refer to the process of transforming a new or updated system design into a function.

VI. RESULTS

Propose simulator is designed using python programming and can provide following features

1) Inbuilt support for AI algorithm which helps in predicting user mobility
2) Can be upgrade with new simulation algorithms
3) Can be used to load simulation parameters from various sources such as dataset CSV files, database etc.
4) User mobility patterns
5) Mobility patterns using geographical maps
6) Detailed handover (HO) process implementation
7) Support 5G simulation

In rest of the paper you can read in depth about above implementation and simulator is still in building process and for learning purpose it will be release soon but not yet publish on internet. Implementing above scenarios in real environment will take lots of infrastructure and cost so author is saying such networks can be tested using this SyntheticNET simulator and upon getting better results can look forward for real implementation

To implement this simulator we designed visual 5G environment where node in cells will choose nearest base station to get cellular services and to detect this nearest base station application will use AI algorithm which works like human brain and human brain will choose shortest path to reach any destination and similarly 5G network will use same shortest path technique to choose best path to reach base station.

To predict mobility DNN and XGBOOST algorithm are used and we also used same algorithms

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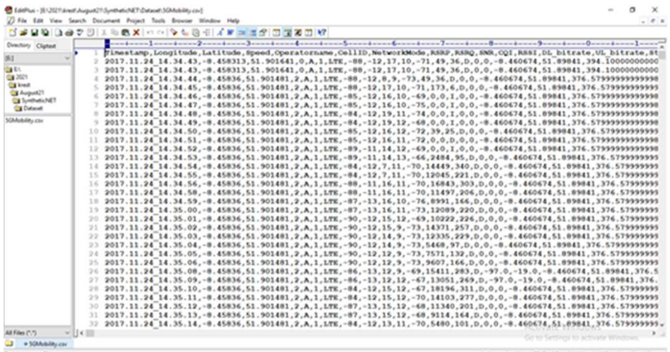
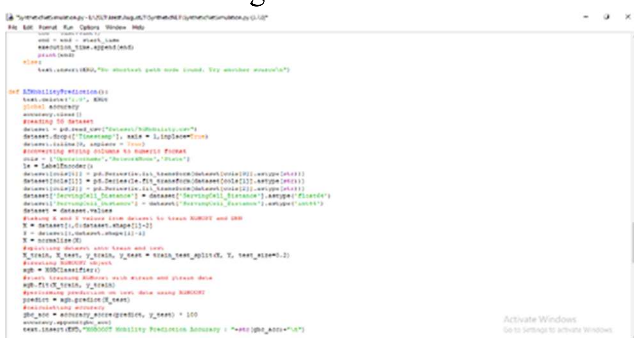
to predict mobility and to calculate this algorithms accuracy we have used 5G network dataset which can be used to train this algorithms and this trained model will be used to predict mobility from test data and correctly prediction percentage of this test data will be consider as algorithm prediction accuracy.

To train this AI algorithms we have used below 5g dataset.



In above dataset we have values like latitude and longitude with nearest LTE server and other values like bandwidth SNR etc. This dataset is used to train AI algorithms

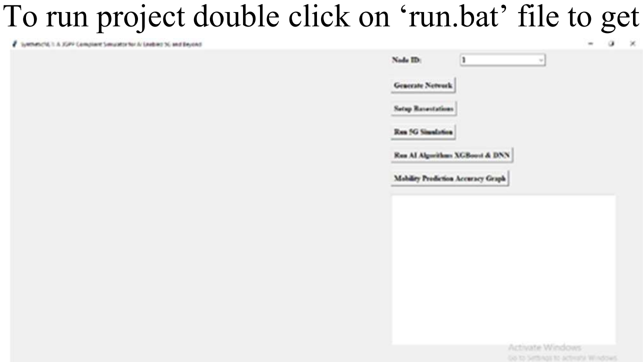
Below code showing with comments about XGBOOST and DNN implementation



In above screen read red colour comments to know about XGBOOST mobility training and DNN algorithm you can see inside 'test.py' file.

SCREEN SHOTS

To run project double click on 'run.bat' file to get below screen



In above screen click on 'Generate Network' button to generate simulation network

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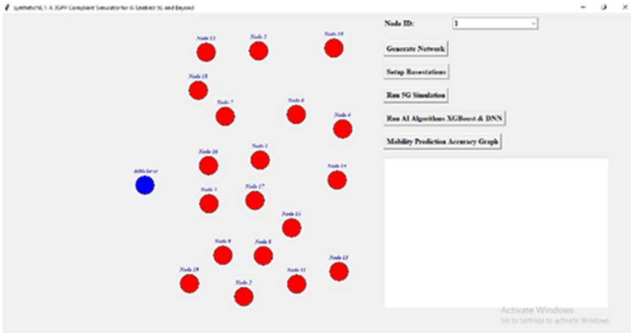
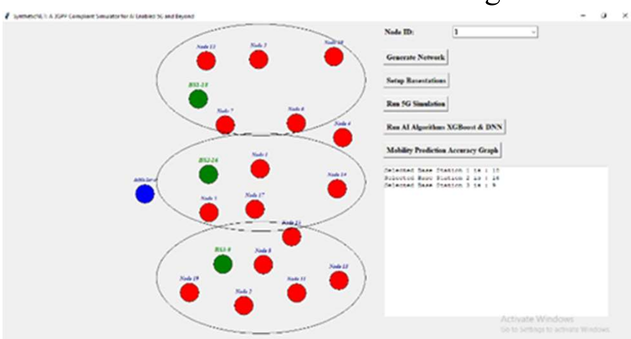
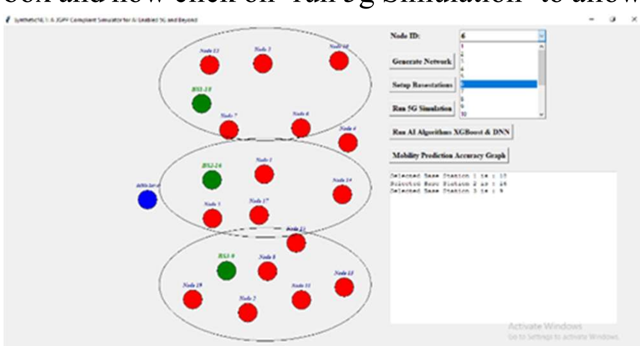


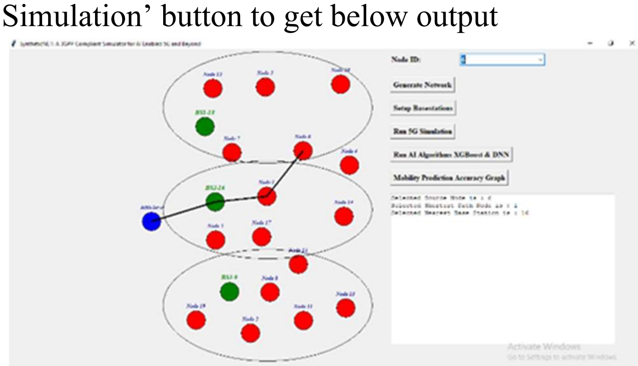
In above screen all red colour nodes are the mobile users and blue colour node is the mobile server which provide services to mobile user and now click on 'Setup Basestation' button to divide network into cells and then assigned base station to each cell



In above screen big size oval represents network cells and green colour node is the base station which connect mobile users to mobile server for services and mobile user will select nearest base station to get services from mobile server. Now select any node from Node ID drop down box and now click on 'run 5g Simulation' to allow mobile user to send request to mobile server



In above screen I am selecting 'Node6' from drop down box and now click on 'Run 5G Simulation' button to get below output



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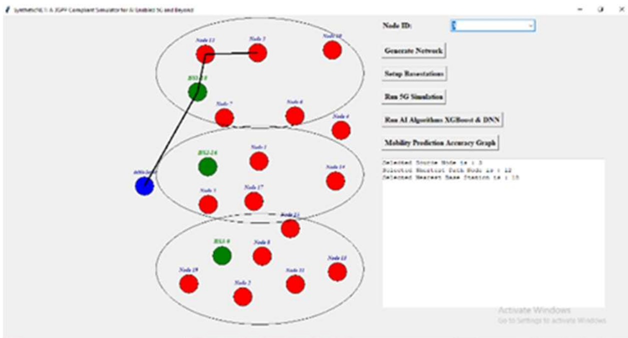
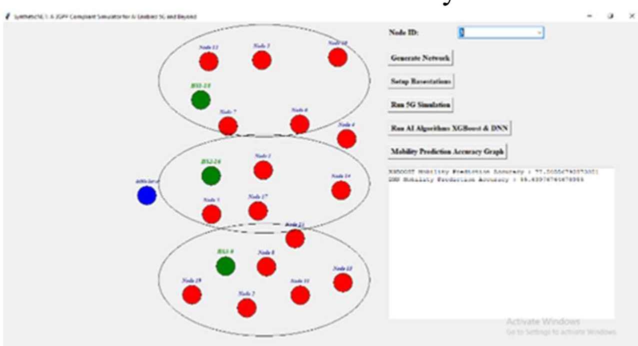
In above screen in simulation we can see node 6 selected nearest neighbour 1 and then nearest neighbour 1 selected nearest base station 'BS2-16' and this base station connect mobile user to mobile server and similarly you can select any mobile user and run 5G simulation. In below screen we can see base station selection for Node3



Now click on 'Run AI Algorithm XGBoost and DNN' button to train AI algorithms with 5G network data and calculate accuracy



In above screen in text area we can see XGBOOST mobility accuracy is 77% and DNN accuracy is 55% and now click on 'Mobility Prediction Accuracy Graph' button to get below graph

In above graph x-axis represents algorithm name and y-axis represents accuracy of those algorithms which is similar to given in base paper like below screen.

VII. CONCLUSION

The currently available templates are bound to make it much simpler, less rational considering and are lacking in the use of key network features that make it insufficient to capture the complexity and power of a real mobile network. To address these challenges, we have

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developed the first compact 3GPP 5G (15th Release) network compiler called SyntheticNET simulator. SyntheticNET provides realistic and effective testing of different network conditions as well as implementation of a few key network features. The SyntheticNET simulator is the first and only template built to date to the model of more than 20 parameters necessary for the use of a detailed HO-based 3GPP process. With additional support for real-time tracking of user traffic, critical KPIs such as maintenance and HO success rate can be accurately assessed. In addition to the mobility, other key components of the SyntheticNET interface include ray-based models to provide accurate signal strength statistics, as well as a flexible frame structure to help meet a few 5G operating conditions (MBB, URLLC, mMTC) and requirements. SyntheticNET simulator is thus the first Python-based template that can easily process, manipulate and analyze large data sets. Similarly, it also has easy access to a wide range of machine learning algorithms. This makes SyntheticNET template much easier to implement and test AI-based solutions for autonomous and efficient network parameters in a wide variety of network applications making it useful for research communities and industries alike.

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