Base Station Allocation using SVM for Load Balancing in Heterogeneous Mobile Cellular Network

Tincy Thomas, Aby Abahai T

Abstract*: The dramatic increase in mobile network subscribers demands high data traffic. This huge data demand is becoming one of the challenges for mobile operators. In cellular communication network, the whole coverage area is divided into cells. The network traffic is not uniformly distributed across base stations in mobile cellular network. This leads to difficulties in network management and load balancing issues arise. To address these challenges small base stations are deployed in network to cope with the explosion in mobile traffic. Cells having large coverage area and transmission power are called macro cells. Small cells contain base stations with small transmission range. If more user equipment are connected to macro cell, it may become heavily loaded and they cannot serve all devices connected to it. In such cases the traffic can be shifted to small cells that are lightly loaded. Support vector machines are used for determining the offloading process. Based on the historic data and the movement of users, resource allocation can be estimated. Base stations are allocated to the users based on several factors like load value, resource utilization, traffic type, cell tower position etc. The main objective of the paper is to balance cellular network traffic by optimizing resource utilization and increase the network throughput.

Index Terms*: Quality of Service(QoS), User equipment(UE), Self-Organizing Network(SON), support Vector Machine(SVM).

I. INTRODUCTION

The number of data users are dramatically increasing day by day. The explosion of mobile internet traffic requires wireless communication systems to support higher data rate. The higher traffic rate consumes network resources very fast. The mobile operators invest a lot of money to improve network capacity in order to guarantee an excellent quality of service (QoS) and high data rates for user equipment (UEs) [1]. All devices should get a fair share of the available resources. So the resource utilization should be optimized to meet the resource demand.

In a wireless communication network, the coverage area is divided into regions called cells. Each cell consists of base stations and antennas for transmitting the signals. Cell coverage area is determined by the strength of the signals. The traffic load is not uniformly distributed among cells. That is, some cells may have higher traffic requests and they lack resources to handle all the incoming traffic from the UEs. While traffic load of some cells may be very less and they have adequate resources to serve more UEs. The load imbalance may affect cell throughput and result in user dissatisfaction. The major challenge faced by the network operators today is to provide satisfactory services to all the users. Cellular networks can be of two types, homogeneous and heterogeneous. Homogeneous network consists of a single layer of cells designed for frequency re-use. In heterogeneous network, cells can be of different coverage area called macro cells and small cells. Macro cells are base stations of large coverage area and small cells are base stations with small transmission range. Traditional wireless networks rely on manual configuration which is very time consuming and expensive. The network associated parameter values can be changed according to traffic condition or when setting up network problem. This may take long delays and may lead to high error rates. Self-organizing network (SON) is a solution to this by selecting and adjusting the network parameters automatically. SON enables the network to adapt quickly on environment changes without human intervention. This requires automatic adjustments of network parameters. The main SON functionalities are self-configuration, self-healing and self-optimization. Self- configuration is done for changing the parameter value. For example, automatic neighborhood relationship planning (ANR). Each cell collects information about all the neighboring cells. If any cell is newly added to the network or deleted from the network, the neighboring cell list should get updated. Handover optimization is an example of self- optimization. Self-healing is done in the case of failures or errors. SON provides a functionality called Load balancing, which hands off UEs from heavily loaded cell to neighboring comparatively less loaded cells to increase the network resource utilization. In heterogeneous network, small cells are deployed to support high data rate services and to improve service quality of cell edge users. The signal strength is weak towards the edge of the cell. Therefore the base station do not server the UEs connected across the cell edge. In such cases the UEs can be served by the neighboring base station which is capable of providing enough resources. Traffic load from large macro cells are offloaded to small cells to improve network performance. The proposed load balancing scheme aims to achieve higher throughput and decrease the number of unsatisfied users. This can be achieved by shifting load from

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heavily traffic cells to neighboring less traffic cells. The deployment of small cells in 5g network enhance cell coverage and handover efficiency. Migration latency can be also reduced during handover. The proposed system prevents the traffic congestion by optimizing the use of base stations.

II. RELATED WORKS

Mobility load balancing is used to address the uneven load distribution problem. The basic idea is that an overloaded cell selects less loaded neighboring cells to offload its traffic. The overloaded cell shifts its edge users to neighboring less loaded cells by handover region adjustment. As the load increases, the cell coverage gradually shrinks. In the literature, several research studies have addressed this issue. Many algorithms have been proposed in order to dynamically adjust the scope of both overloaded and under loaded cells. A typical transfer approach to implement load balancing is proposed by M.Dottling and I. Viering [2]. The cell that has the highest physical resource block utilization ratio is selected as the source cell and the cell having the lowest utilization ratio as target cell. Yao Tien Wang et al. [3] proposed a method where an overloaded cell (hot-spot cell) trying to borrow resources to the least loaded neighboring cells and is based on neural networks and fuzzy logic. Load balancing can also be done by transferring excess traffic from overloaded cell to the least loaded neighboring cells by dynamically adjusting the handover parameters or using the cell breathing technique. The principle of such technique is to gradually shrink the cell coverage as the load increases. A method of estimating the load after handover completion is proposed by Andreas Lobinger et al. [4]. This method is based on the signal to interference plus noise ratio prediction and the measure of the user signal quality. Most of the studies have addressed traffic balancing in homogeneous networks consisting cells of equal coverage range. Atayero et al. presented a neural-fuzzy model to adjust the hysteresis handover parameter to force UEs at the cell edge to reselect a less loaded cell [5].

Mobility load balancing technique for a homogeneous network is proposed by A.Roshdy et al. [6]. Handover parameters are adjusted to achieve load balancing. Cell load is estimated based on its resource utilization factor. Cell individual offset (CIO) is the mobility parameter optimized for load balancing based on resource utilization, traffic distribution and soft handover success rate [6]. For each cell the required resources to achieve target throughput are calculated. The traffic shifting is done by comparing the required resources with current resource utilization. This can be done by varying parameters like cell border width or cell transmission power. The cell border can be decreased for overloaded cell and increased for less loaded cells. Cell offset is automatically adjusted according to the load of the source cell and that of the target neighboring cell.

A self organized structure for mobility management in wireless network is proposed in [7]. Nodes in wireless network can change its neighbors by varying transmission power. In SH approach each node broadcasts its parameters to all the neighbors and store its distance from each node. Node chooses the next hop node for communication based on neighboring nodes' parameters. In the case of failures, SH node can choose alternate routing paths. In power efficient topology control approach, nodes can assign varying transmission power corresponding to each neighboring node[7]. This paper proposes SH algorithm and algorithm for topology structure.

III. PROPOSED WORK

A load balancing mechanism is proposed for a heterogeneous mobile cellular network. The network capacity has to be increased due to the high data demand. The load balancing can be achieved by allocating the base stations to UEs optimally. Small cells are deployed in macro cells forming a heterogeneous network to extend service coverage. Machine learning approach is used in the proposed load balancing scheme. Resource allocation is done by support vector machines (SVM). Each user is allocated based on SVM result. The information required by the classifier includes cell type (macro or small cell), data demand, load value, proximity of users with each base station (BS) and information about the trans-mission channels. These features are then used to train SVM to allot the base stations for users. If the macro cell lacks resources to serve the UEs, the traffic load can be shifted to small cells having less traffic and vice versa. BS activation can be done by predicting the traffic pattern to reduce energy consumption. The underutilized resources can be allocated to users. The future offloading decisions can be predicted and a wireless communication network can be simulated showing load balancing among macro cell and small cells. Existing load balancing systems are based on homogeneous networks. Proposed system relies on heterogeneous mobile cellular network. The existing load balancing mechanisms take more time since it require frequent calculations. The proposed system trains historical data and predict future offloading decision which make use of advantages of machine learning.

A. Self-Organizing Network

SON is designed to make the planning, configuration, optimization and management of mobile communication networks. These networks continuously interact with the environment and take decisions independently. The main functionalities of SON are self-configuration, self-optimization and self-healing.

Self-Configuration

In order to make the network operable, it should be configured automatically. The functionalities include configuration of individual base station parameters and other network parameters. Self-configuration is done when there is any failure of base station or during the deployment of new devices. Manual configuration can be reduced by this feature. ANR is automatic neighborhood relationship which automatically configures the parameters associated with neighboring base stations.

Self-Optimization

Base stations and network parameters are continuously optimized in order to guarantee an optimal performance. It includes coverage and capacity optimization, handover parameter optimization, load balancing, resource

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optimization and coordination of SON functions. Self-optimization functions can ensure optimal performance of the network by continuously monitoring the system and gathering information by using reported measurements. In the case of load balancing, cell individual offset is optimized.

Self-Healing

Self-healing function is activated whenever a fault or failure occurs. This can be either software or hardware malfunction. Manual healing of cellular network is very difficult and time consuming. The objective of SON self-healing mechanism is to ensure recovery. The hardware can backup its own data. It detects and diagnose the failure and also trigger compensation mechanisms. The network can return to function properly after troubleshooting.

B. SON Architecture

SON architectures can be of three types based on scalability, stability and agility.

- Scalability: It is the ability of the network to reduce complexity and to provide good performance even for large scale systems.
- Stability: A network is said to be stable if it do not results in ping-pong phenomenon during handovers.
- Agility: It is the capability to adapt easily to changes. But the temporary changes do not affect the network. Lack of agility may result in instability.

Centralized SON Architecture (C-SON)

In the C-SON architecture, functionalities are controlled by network management system (NMS) . The main advantage of this architecture is that it can gather information from all network entities. It optimizes the parameters of all centralized SON functions and provide an overall optimization enabling stability. The C-SON architecture also facilitates coordination between the SON functions. It gives a global view of the whole network. Slow response times, high backbone traffic and a singular point of failure are disadvantages of this architecture.

Decentralized SON Architecture (D-SON)

In D-SON architecture, functionalities are executed in the network nodes. The messages are exchanged directly between nodes. D-SON architecture provides more dynamic for SON features. It adapts more quickly to changes in the network. But optimizations are not global and therefore cause instabilities. In D-SON, the control is on each cell in the network.

Hybrid SON Architecture (H-SON)

The H-SON architecture executes SON algorithms both in the NMS at the level of network elements. H-SON take advantages of both C-SON and D-SON and overcome their disadvantages.

C. Heterogeneous Network

Effective network planning is essential to meet the data demand of subscribers. Existing measures are not sufficient to meet this challenge. The solution is to add small cells to an existing network. Thus the traffic load can be spread across different base stations within a network. Small cells increase overall network capacity by providing data to UEs that are not served by the macro network. If the macro cell is not capable of serving all the UEs connected to it, then the traffic can be offloaded to small cells. Deployment of small cells increases performance and service quality. Small cells are less susceptible to interference and higher signal quality leads to better throughput. The proposed method enables the users to transmit and receive at higher data rates. It is inexpensive too.

D. CDR

Data collected from Call Detail Records (CDRs) are used for training and testing the proposed model. CDR contains the information about the users like mobile equipment identity number (UE ID), ID of the base station to which UE is connected, base station position coordinates etc. It also contains information about the channels used for the transmission of the signals and many network associated parameters. Service providers make use of all these data for analyzing network traffic and to take necessary actions to increase their expenditures. Other cellular communication details load value, resource utilization factor, power and energy associated with each base stations in the network, traffic type (data or voice) are also extracted from the data provided by the service providers. These traces can be used to predict the communication behavior. The traffic patterns are analyzed to prevent traffic congestion by allocating necessary resources to the unserved UEs. Resource allocation is optimized to guarantee QoS and enhance overall network throughput.

E. Classification Model

SVM is a supervised machine learning algorithm used for classification. In SVM each features are plotted as vectors in high dimensional space and they are called support vectors. SVM reduces training time since it uses only support vectors for training instead of loading the entire dataset. SVM performs classification by defining a margin between data instances of different classes. The accuracy of the classifier increases as the distance between each data instance and margin increases. Wider margin indicates better classification results and minimum error. Thus it reduces over fitting. Wider margin indicates better classification results and minimum error. Given a data set {xi, yi}; i =1,…,m where yi represents the label and xi represents the training vectors. Building a classification model consists of training and testing phase. After training the model testing is done to evaluate the performance of SVM.

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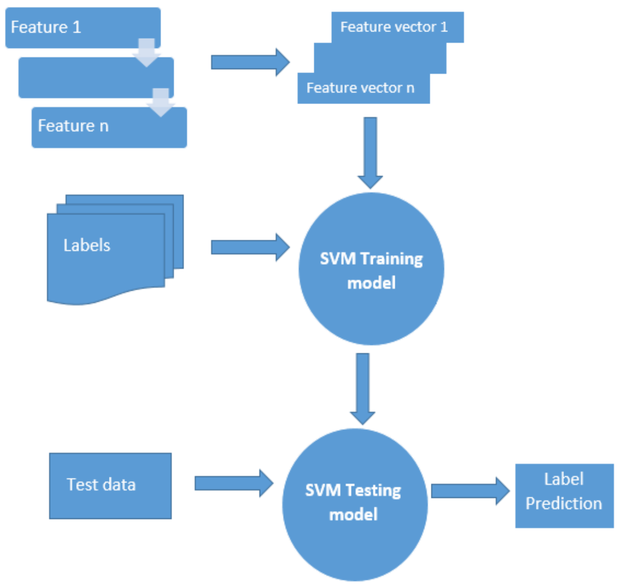

Fig. 1. SVM Learning Model

Preprocessing Stage

Data Preprocessing is the primary step in machine learning to make the data suitable for classification. The data associated with the cellular communication can be inconsistent or unstructured. Such data compromises the performance of classifiers. Therefore prior to classification, data is preprocessed. The redundant data can be removed and data normalization is performed.

Preprocessing includes cleaning, integration, transformation, reduction and discretization of data. Some data may lack attributes. Such missing data can be added and outliers or discrepancies can be removed in data cleaning step. Data in different ranges are difficult to process. Therefore data is scaled to make all the attribute values to fall within a specific limit. The attribute value X in [X_{min} , X_{max}] can be normalized to X' by using the following formula

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Feature Selection Stage

The training dataset may contain unwanted features or features that do not have direct impact on output prediction. Feature selection is done to remove the redundant and irrelevant features. The final dataset contains 12 attributes and 1000 instances.

Classification Stage

The proposed system uses supervised learning for classification. It consists of training and testing phases. Machine learns during training phase using training dataset. SVM is trained with attributes such as cell type(whether the cell is macro or small cell), geographical position of cell tower (gives proximity of users with each BS), load value, channel quality indicator, estimation of current data demand, data type (voice, video or data), user id, cell id, resource block utilization (RBU), received total wideband power (RTWP). RTWP is the total level of noise within the frequency band of any cell. A model is constructed by training the machine with all the features. During testing, a test dataset is created by hiding the labels corresponding to all the features and given as input to SVM to classify data instances. The model predicts the output labels based on the facts it learned during training phase.

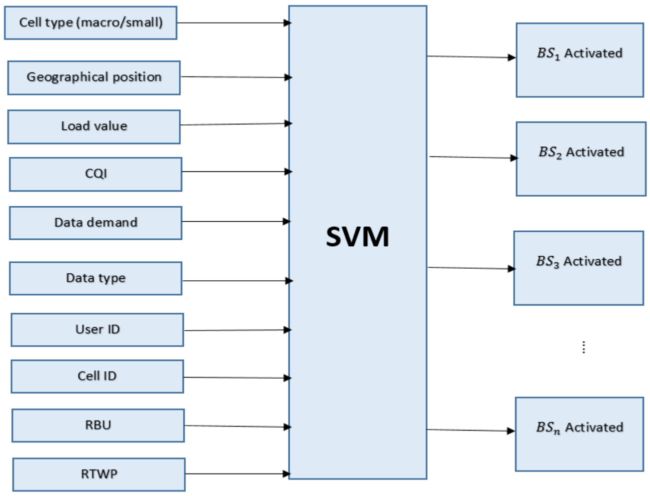

Fig. 2. Proposed System

IV. RESULTS

Network is simulated using Matplotlib. Matplotlib is a python library used to create simulations by using python scripts. It has a module named pyplot which is used for plotting by providing feature to control line styles, font properties, formatting axes etc. NumPy is an open source alternative for MatLab. SimPy is a good option for discrete level simulation. All the simulation components like base stations, users, resources etc are modeled by using Simpy. The simulation of the heterogeneous network consisting of one macro base station and four small base station is shown below.

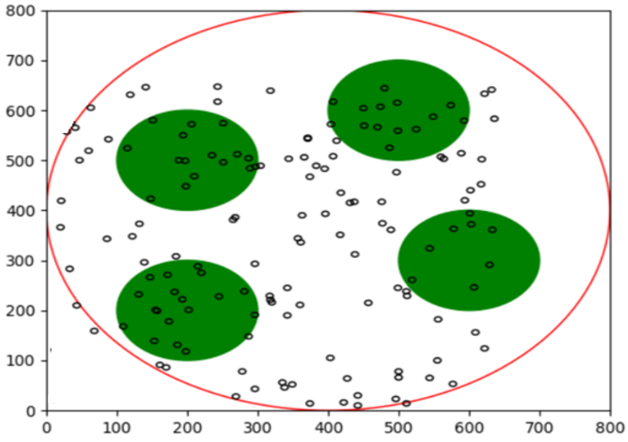

Fig. 3. Heterogeneous Network Simulation

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Load Is Getting Heavy :: 149
Load Is Getting Heavy :: 150
Base Station1 Activated :: 151
Base Station1 Activated :: 152
Base Station1 Activated :: 153
Base Station1 Activated :: 154
Base Station1 Activated :: 155
Base Station4 Activated :: 156
Base Station3 Activated :: 157
Base Station3 Activated :: 158
Base Station1 Activated :: 159
Base Station2 Activated :: 160
Base Station3 Activated :: 161
Base Station2 Activated :: 162
Base Station2 Activated :: 163
Base Station2 Activated :: 164
Base Station1 Activated :: 165
Base Station1 Activated :: 166
Base Station3 Activated :: 167
Base Station4 Activated :: 168
Base Station3 Activated :: 169
Base Station2 Activated :: 170
Base Station4 Activated :: 171
Base Station4 Activated :: 172
Base Station1 Activated :: 173
Base Station4 Activated :: 174
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Fig. 4. Base Station Activation

V. PERFORMANCE ANALYSIS

The performance evaluation can be carried out by comparing the performance metrics of SVM classifier. Machine learning framework Scikit-learn is used for the implementation which provides a range of supervised and unsupervised learning algorithms through a consistent interface in Python. SVM increases the performance and achieves 100% accuracy with reduced False Alarm Rate. The following are the metrics used for performance evaluation.

- TP= True Positive
- TN= True Negative
- FN= False Negative
- FP= False Positive
- True Positive Rate (TPR) = TP / (TP + FN)
- True Negative Rate (TNR) = TN / (FP + TN)
- False Negative Rate (FNR) = FN / (FN + TP)
- False Positive Rate (FPR) = FP / (FP + TN)
- Accuracy = (TP + TN) / (TP + TN + FN + FP)

Table 1. Performance Metrics

TPR	FPR	Precision	Recall	F-Measure	MCC	ROC	PRC
0.857	0.429	0.667	0.857	0.750	0.447	0.714	0.643
0.571	0.143	0.800	0.571	0.708	0.447	0.714	0.657
Weighted AVG.							
0.786	0.214	0.792	0.786	0.785	0.557	0.786	0.726

Table 2. Classification Result Summary

Description	Result	%
Time taken to build model	0.02s	
Total Time of Completion	0.017s	
Correctly Classified Instances	10	71.4286%
Incorrectly Classified Instances	4	28.5714 %
Kappa statistic	0.4286	
Mean absolute error	0.2857	
Root mean squared error	0.5345	
Relative absolute error		55.5556%
Root relative squared error		103.8815%
Total Number of Instances	14	

VI. CONCLUSION

A load balancing scheme for heterogeneous mobile cellular network is proposed. The heterogeneous network consists of a macro cell and within the macro cell there are small base stations. Macro cells are high power base station and are capable of serving more user equipment. Small base stations have small coverage area and they are deployed to balance the load across the network. The proposed method enhances the capacity of the cellular network by increasing the throughput of each cell. The proposed method optimizes resource allocation by forecasting the network traffic. The offloading decision is based on the decision made by the SVM classifier. The resources requested by the overloaded cells are provided by the lightly loaded cell. When the number of user equipment exceeds a particular limit, then the macro cell may get congested and it cannot provide services to some users. These user equipment are then served by the small base stations deployed within the macro base station. Whenever the load balancing problem occurs the small base stations have to be activated. Initially these base stations may be in off mode. So switching have to be done in accordance with the traffic condition. The users are allocated base stations based on several factors like load value, resource utilization, traffic type, cell tower position etc. The goal of this mechanism is to minimize operational effort and expense and to achieve load balancing.

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