Joint Load balancing and Spatial-temporal Prediction Optimization for Ultra-Dense Network

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***Abstract*—To meet the further explosive capacity demand, network densification is a promising technology. The load imbalance between cells in an ultra-dense heterogeneous network is a major challenge, which seriously affects the performance of the system. Existing load balancing (LB) methods usually operate in reactive mode. The parameters of the cells are adjusted reactively according to the dynamic changes of network load. The inherent reactivity of existing LB schemes undermines the quality of experience (QoE) in 5G and beyond. To solve this problem, we propose a mobility management framework for load balancing, which turns the original reactive load balancing into forward-aware and active. The simulation results show that the proposed method can better optimize the network performance and realize the intelligent mobile management for the future network.**

***Index Terms*—5G and beyond, proactive load balancing, heterogeneous network, soft load**

I. INTRODUCTION

According to the Ericssion mobility report, the number of mobile phone users will reach 7.5 billion and global total mobile data traffic is projected to grow by a factor of around 4.5 to reach 226EB per month in 2026 [1]. The future wireless networks are required to provide explosive capacity, extreme low latency and massive connections. To meet such stringent quality of service (QoS) requirements, network densification is considered as one of the promising technologies.

Due to the mobility of user equipments and coverage limitation of small cells, the load on the small cell network often becomes unbalanced. The unbalanced network load will lead to decrease in network throughput and handover success rate, and even result in radio link failure (RLF). It becomes an important issue to ensure load balancing among neighboring cells. Mobility load balancing (MLB) can balance the load between ultra-dense cells. An adaptive mobility load-balancing algorithm was proposed to adjust handover parameters depending on the overloaded cells and adjacent cells in [2]. The authors in [3] put forward a load balancing strategy in green heterogeneous network, but it redistributes the users to other cells according to current network load, which leads to extra cost and user equipments handoff. However, these load balancing methods are reactive, and their optimized parameters often fail to keep up with the rapid changes of load distribution in the dynamic Ultra-Dense Network (UDN).

The problem with the existing method is that load balancing does not consider the future load of the cells, but only performs LB based on the current load. If the future location of users is predicted, the network can be proactive in redistributing the network load and adjusting network parameters to achieve the goal of improving network performance.

According to the research results of [4], the predictability of user mobility can be as high as 93%. Scholars have conducted extensive research on location prediction [5], most of which are committed to using machine learning to predict the user's next arrival cell [6], [7]. The authors in [8] proposed a robust location prediction method based on activity patterns. Recently, H. Farooq and A. Imran used Semi-Markov model for spatio-temporal mobility prediction in LTE [9]. Researchers have tried to optimize network resource allocation through mobility prediction. S. Tian et al. proposed a mobility prediction based on decision tree and Markov model to optimize network load balancing in hot spots [10]. H. Farooq and A. Asghar proposed an active load balancing framework "OPERA" for ultra-intensive networks based on mobility prediction [11]. However, the accuracy of their prediction models is not high enough, which affects the performance of load balancing algorithms, and their load balancing algorithms are not realized by adjusting cell individual offset (CIO), which can quickly realize network load balancing.

This paper proposes a forward-looking and active load balancing scheme. First, the Bayesian Additive Regression Tree (BART) model is used to predict the spatial and temporal mobility of users, and the user's location is predicted with the cycle of one week. Secondly, by predicting the users'mobility, the future load of cells is estimated. When load balancing is performed, it is no longer only based on the current load, but the future load is also taken into account. Finally, a heuristic load balancing logarithm is proposed by adjusting the CIO according to both the current and the future cell load. Through forward-looking of the load distribution, the pre-allocation of network resources will be more intelligent and efficient, thereby improving the robustness of user movement and the network performance.

The rest of this paper is organized as follows. Section II describes the system model. The proposed method is provided in Section III. Section IV discusses the simulation results and the performance of the proposed algorithm. Finally, Section V concludes the paper.

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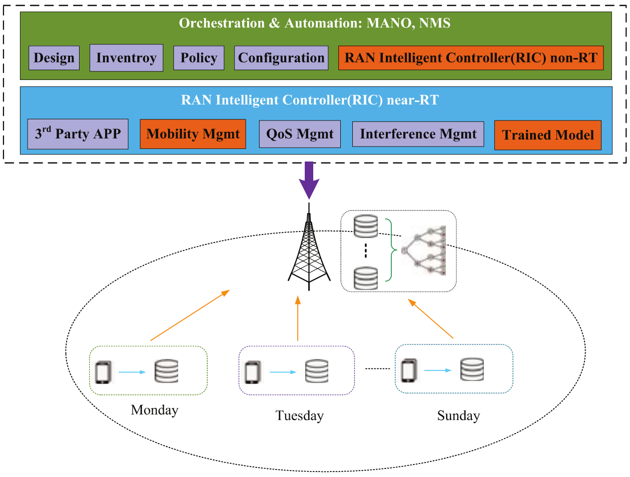

Fig. 1. System architecture based ORAN.

II. System Model

A. Network Model

The system model is based on open RAN (O-RAN) architecture [12] depicted in Fig.1. This paper studies the heterogeneous network model of 5G and beyond. The small cells provide users with data traffic services, while macrocells are responsible for basic coverage and provide control signaling, all the cells are consistent with the O-RAN architecture. The proposed framework is designed and implemented in three function, which are RAN intelligent controller (RIC), non-real time, mobility management, and trained model.

The RIC periodically in Macrocell collects information from small cells, and if any overloaded cells are detected, they will optimize and update the handover parameters of small cells to redistribute the network load.

Assuming that the serving cell of user u is cell i, $L_{u,i}$ represents the path loss from the user u to cell i, the transmit power of cell i is P_i, and the signal power received by the user from cell i is $R_{u,i}$, defined as

$$R_{u,i} = P_i L_{u,i} \tag{1}$$

We assume that the Gaussian white noise power spectral density is n_0. The cell bandwidth is B_{cell}, and it is assumed that the bandwidth of all cells is the same. The signal to interference plus noise ratio (SINR) of the user u is shown in formula (2).

$$S_{u,i} = \frac{P_i L_{u,i}}{n_0 B_{cell} + \sum\limits_{j \neq i} R_{u,j}} \tag{2}$$

The number of used resource blocks is taken as a measurement of cell load. The number of physical resource blocks (PRB) required by user u can be calculated by

$$N_u = \left\lceil \frac{D_u}{C_u \mathrm{BW}_{\mathrm{PRB}}} \right\rceil \tag{3}$$

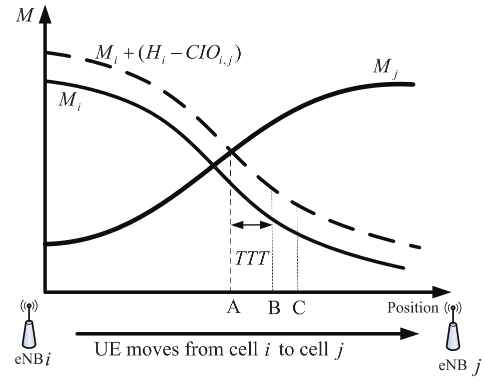

Fig. 2. Event A3 in NR.

where D_u represents the rate requirement of user u, and C_u represents the spectrum efficiency. $\mathrm{BW}_{\mathrm{PRB}}$ denotes the bandwidth of each PRB (in Hz). Let $\sum N_{u,i}$ and U represents the number of PRBs allocated and users in cell i, respectively. Then, the load of cell i can be expressed as:

$$\rho'_i = \frac{\sum_{u=1}^{U} N_{u,i}}{B_{\mathrm{cell}} / \mathrm{BW}_{\mathrm{PRB}}} \tag{4}$$

B. Handover Process

The 3GPP A3 event shows the flow of the handover (HO). As shown in Fig.2, if the following condition (5) is met within a specific time interval (time to trigger), HO is triggered.

$$M_j > M_i + (H_i - \mathrm{CIO}_{i,j}) \tag{5}$$

where M_i and M_j respectively represent the received signal strength from cell i and cell j. H_i is the hysteresis parameter for the A3 event. $CIO_{i,j}$ is the cell individual offset (CIO) set by cell i for cell j , which is the switch parameter adjusted in this scheme to achieve load balancing among cells.

As shown in Fig.2, when the condition of is met at point A , the event A3 begins to enter, and continues to satisfy for a period of TTT, while user equipment (UE) moves from point A to point B. UE starts switching at point B and completes the switching process at point C.

C. Mobility Load Balance

The purpose of MLB is to balance the load between adjacent cells [13]. MLB has the following three working modes:

(1) Relax the handover condition so that UEs can switch from the overloaded cell in advance to its neighboring cells.

(2) The handover condition is tightened to delay UEs switching from neighboring cells to overloaded cell.

(3) Perform the above two methods at the same time.

D. Allowable Range for CIO

Introduced in the 3GPP standard, the main goal of Mobility robustness optimization (MRO) is to reduce RLF rate and the number of unnecessary handovers [14]. Too early handover

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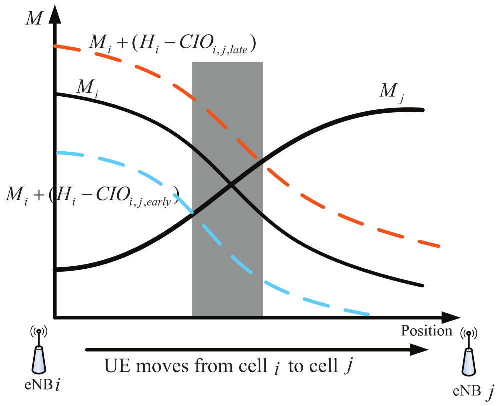

Fig. 3. Allowable range of MLB

and too late handover will cause RLF, And unnecessary handover results in ping-pong behaviour.

MLB strives to redistribute the load between neighboring cells with the goal of balancing the network load by adjusting parameters such as CIO. Inappropriate action of MLB may cause handover problems such as too early handover or too late handover. If MLB can adjust the handover parameters correctly, handover problems will not occur, so conflicts with MRO can be avoided. Related researches have been done on the allowable range of handover parameters for MLB in existing schemes [14]. As the shaded part shown in Fig.3, the allowable ranges of CIO are as following:

$$CIO_{i,j} \leq CIO'_{i,j} \leq CIO_{i,j,early} \tag{6}$$

$$CIO_{j,i,late} \leq CIO'_{j,i} \leq CIO_{j,i} \tag{7}$$

where $CIO'_{i,j}$ and $CIO'_{j,i}$ are the adjustments of $CIO_{i,j}$ and $CIO_{j,i}$ respectively after the operation of MLB. $CIO_{i,j,early}$ is the critical value of CIO that make UEs handover too early, in other words, when $CIO'_{i,j}$ is greater than $CIO_{i,j,early}$, too early handovers may occur. $CIO_{j,i,late}$ is the critical value of CIO that make UEs switch too late, in other words, when $CIO'_{i,j}$ is less than $CIO_{i,j,late}$, too late handovers may occur.

III. Proposed Scheme

A. Mobility prediction

As described above, to provide efficient resource and mobility management of the network, it is of great importance to predict users' location, i.e the trajectory or the next arrival cell of the user. In this section, we propose to predict the users' location based on the BART [15]. BART is a recent statistical method that combines ensemble learning and nonparametric regression. Recently, BART has gained popularity among the research community with numerous applications such as biomarker discovery in proteomic studies, estimating indoor random concentrations, predicting power outages during hurricane, prediction of trip durations in transportation and so on [16]. One of the primary advantages of BART is that it can provide straightforward uncertainty quantification for prediction, i.e standard error and intervals of the prediction. For the location prediction, if we can predict the intervals of the user's locations, it will help us to design more robust MLB and handover scheme to improve the resource management efficiency. Moreover, it is demonstrated to perform better than or competitively with some state-of-the-art techniques including random forests and boosting [17]. BART is a Bayesian regression approach that aims to predict an output y using a p dimensional vector of inputs $\mathbf{x} = [x_1, \cdots, x_p]$. It is accomplished by using a sum-of-trees, specifically, a BART model with $\tilde{M}$ trees is given by

$$y = \sum_{i=1}^{m} T_i(\tilde{M}_i; x_i) + \epsilon_i \tag{8}$$

where $T_i(\tilde{M}_i; x_i)$ denotes a decision tree structure with b terminal nodes $\tilde{M}_i = (v_{1,i}, v_{2,i}, \cdots, v_{b,i})$, which are dependent on the input vector x_i and ϵ_i represents independent normal random error with mean 0 and variance σ^2.

For the considered problem, the y corresponds to the users' location at time $t+n$, which is the 3-dimensional or 2-dimensional coordinates $(y_1(t+n), y_2(t+n), y_3(t+n))$, and the inputs $\mathbf{x}$ stand for the history location, moving speed, cell transition history, users' behavior pattern as well as received signal strength, these information can be collected by the global positioning system (GPS), BeiDou (Compass) Navigation Satellite System, sensors in the smart phone and base station. All of these data are collected and classified from Monday to Sunday, respectively. Accordingly, the predicted user's location is classified from Monday to Sunday, respectively. Obviously, some of the inputs, such as the user movement, users' behavior pattern and received signal strength are highly correlated. However, we do not need to consider this effect in our model inputs, since the BART is able to handle the multi-way interactions without much explicit input from researchers.

BART model contains three stochastic components, i.e. the residual error ε_i with variance σ^2, the tree structures $T_1, \cdots, T_{\tilde{M}}$, and the corresponding leaf node values $\tilde{M}_1, \cdots, \tilde{M}_m$. We need to construct probabilistic distributions that assign prior probability to all possible sum-of-trees. For the sake of simplicity, we assume a priori between trees, leaf nodes conditioned on trees, and the residual variance are independent, which is derived in [15]

$$\begin{aligned} p\left((T_1, \tilde{M}_1), \cdots, (T_m, \tilde{M}_m), \sigma\right) &= \left[\prod_j p(T_j, \tilde{M}_j)\right] p(\sigma) \\ &= \left[\prod_j p(\tilde{M}_j|T_j) p(T_j)\right] p(\sigma) \end{aligned} \tag{9}$$

and

$$p(\tilde{M}_j|T_j) = \prod_i p(v_{i,j}|T_j) \tag{10}$$

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For $p(T_j)$, the probability that a node at depth d is nonterminal, determined by.

$$\alpha(1+d)^{\beta}, \alpha \in (0,1), \beta[0,\infty) \tag{11}$$

From (11), we can control the size of the tree through adjusting the parameters α and β. In our simulation, we set $\alpha = 0.95$ and $\beta = 2$.

For $p(\sigma)$, the inverse chi-square distribution can be, i.e. $\sigma \sim v\lambda/\chi_v^2$. The two hyperparameters v, λ can be obtained from the data prior approach.

BART can be easily calculated by backfitting Markov chain Monte Carlo (MCMC) algorithm. The inputs of the prediction includes: (1) daily averaged history location, moving speed, cell transition history, users' behavior pattern and received signal strength. (2) the periodicity of the data is one week. In the prediction, 80% of the samples are used to fit the model and 20% of the samples are used to test the prediction.

B. Soft load prediction

Forecast the distribution of users in the network in the future, and predict the load change of cell i after a period of n. Assuming that the current time is t, then the load change of cell i during the period of $[t, t+n]$ is given by:

$$\Delta\rho_i\left(t+n\right) = \frac{\sum_{q=1}^{Q} N_{q,i} - \sum_{k=1}^{K} N_{k,i}}{B_{\text{cell}} / \mathrm{BW}_{\text{PRB}}} \tag{12}$$

where q is the possible new users for cell i during the period of $[t, t+n]$, and Q is the total number of new arriving users for cell i. k is the users that will leave from cell i during period of $[t, t+n]$, and K is the total number of leaving users. We define soft load as the current load plus the future load change. Thus, the soft load of cell i is given by

$$\begin{aligned} \rho_i\left(t\right) &= {\rho'}_i\left(t\right) + \Delta\rho_i\left(t+n\right) \\ &= \frac{\sum_{u=1}^{U} N_{u,i} + \sum_{q=1}^{Q} N_{q,i} - \sum_{k=1}^{K} N_{k,i}}{\mathrm{B}_{\text{cell}} / \mathrm{BW}_{\text{PRB}}} \end{aligned} \tag{13}$$

C. Adjustment of CIO

According to the part C of section II, the network load can be balanced through adjusting CIO. We assume that cell i has heavy load and its neighbor cell j has light load. The MLB function in cell i will choose cell j to balance the load and relax the handover conditions by adjusting $CIO_{i,j}$ larger to ${CIO'}_{i,j}$. Meanwhile, cell i informs cell j to adjust $CIO_{j,i}$ lower to ${CIO'}_{j,i}$. Let $\Delta_{i,j}$ and $\Delta_{j,i}$ be the adjustment steps of $CIO_{i,j}$ and $CIO_{j,i}$, respectively, which are calculated as

$$\Delta_{i,j} = \left(CIO_{i,j,early} - CIO_{i,j}\right) \bullet \frac{\rho_i\left(t\right)}{\rho_j\left(t\right)} \tag{14}$$

$$\Delta_{j,i} = \left(CIO_{j,i} - CIO_{j,i,late}\right) \bullet \frac{\rho_i\left(t\right)}{\rho_j\left(t\right)} \tag{15}$$

Then we get

$${CIO'}_{i,j} = CIO_{i,j} + \Delta_{i,j} \tag{16}$$

$${CIO'}_{j,i} = CIO_{j,i} - \Delta_{j,i} \tag{17}$$

TABLE I
SOFT LOAD-BASED MLB ALGORITHM

Algorithm I:

For time t do
Initialization: Predict the location distribution of users at the future time $t+n$, calculate $\Delta\rho_i(t+n)$, ${\rho'}_i$, $\rho_i(t)$, $Thresh_{\text{heavy}}$ and $Thresh_{\text{light}}$.
for i=1 to N **do**
  if $\rho_i(t) \geq Thresh_{\text{heavy}}$ **then**
    put cell i into set $\mathcal{H}$.
    else if $\rho_i(t) \leq Thresh_{\text{light}}$ **then**
      put cell i into set $\mathcal{L}$.
    end if
  end if
end for
for each cell i in $\mathcal{H}$ **do**
  find all the neighbor cells of cell i in $\mathcal{L}$, and then put them into set $\mathcal{N}_i$.
  for each cell j in $\mathcal{N}_i$ **do**
    Use Eq. (14) and Eq. (15) to calculate the $\Delta_{i,j}$ and $\Delta_{j,i}$.
    Use Eq. (16) and Eq. (17) to compute the ${CIO'}_{i,j}$ and ${CIO'}_{j,i}$.
    Modify ${CIO'}_{i,j}$ and ${CIO'}_{j,i}$, Perform users handover between cell i and cell j.
  end for
end for

D. Load Balancing Threshold

For more effective load balancing, two load-balancing thresholds, $Thresh_{\text{heavy}}$ and $Thresh_{\text{light}}$, are introduced in this paper, which vary with the network load. They can be given by

$$Thresh_{\text{heavy}} = \eta \frac{1}{N} \sum_{i \in N} \rho_i(t), \eta \in \left(1, \frac{1}{\overline{\rho}_{\text{net}}^t}\right) \tag{18}$$

$$Thresh_{\text{light}} = \gamma \frac{1}{N} \sum_{i \in N} \rho_i(t), \gamma \in [0,1] \tag{19}$$

where $Thresh_{\text{heavy}}$ is the threshold of overloaded cell, that is, when the load of cell i is higher than $Thresh_{\text{heavy}}$, cell i is heavy and needs to off load to its neighbor cells. $Thresh_{\text{light}}$ is the threshold of light-load cell, in other words, when the load of cell i is lower than $Thresh_{\text{light}}$, it can be selected as the target cell for load balancing. N is the number of cells. η and γ are the load balancing factors. $\overline{\rho}_{\text{net}}^t$ is the network average load at time t, which is given by

$$\overline{\rho}_{\text{net}}^t = \frac{1}{N} \sum_{i \in N} \rho_i(t) \tag{20}$$

E. Proposed Heuristic Load Balancing Algorithm

In this paper, our aim is to balance the load of the whole network. Since the load balancing problem is usually formulated as a user-cell reassociation optimization problem, which is a mixed integer problem (MIP). The integer variables make the problem non-convex and very difficult to solve. For this reason, we propose a heuristic load balancing scheme that achieve LB among cells. The procedure is depicted in Algorithm I.

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TABLE II
SIMULATION PARAMETERS

Parameters	Value
Base station	7 Macro Cells with 3 sectors per Base Station
Number of Small Cells	21 (One per Sector)
Cell radius	500m
Carrier frequency	3.5GHz
System bandwidth	100MHz
Transmit power of Macro cell	46(dBm)
Transmit power of Small cell	23(dBm)
Number of UEs	100 Mobile(20 Pedestrian,80 Vehicle) 300 Stationary
UE mobility speed	Pedestrian(1m/sec), Vehicle(15m/sec)
Hysteresis	3dB
Time-to-trigger	480 msec

IV. SIMULATION AND PERFORMANCE ANALYSIS

In this section, we first describe the simulation scenario. Then we evaluate the performance of our proposed scheme by comparing with the existing method [10].

A. Simulation settings

The simulation is based on a system-level simulation platform built by Matlab. The simulation platform includes UE module, eNodeB module, topology module and motion module. The UE module includes access, measurement, RLF judgment, information reporting and handover function; eNodeB module includes access control, packet scheduling, handover control, MRO and MLB functions. As shown in Fig.1 , there are 7 macro base stations (7 eNodeBs) in the simulation topology. Each eNodeB is composed of three sectors. Each sector has a small base station, and the locations of the small base stations are randomly distributed. The system parameters are shown in Table II. In order to model a real network, users are unevenly distributed in the coverage area. Therefore, some users gather around the hot spots in each sector. Based on in-depth analysis of pros and cons of mobility models, such as SLAW, SMOOTH and Truncated Levy Walk etc., [18], we choose SLAW (Self-similar Least Action Walk) [19] mobility model due to its more realistic nature. Monte Carlo simulation is used to evaluate the performance of the proposed scheme. γ is set as 0.5 while η is 1.2.

B. Simulation results

Comparing with the conventional MLB method [10], we evaluate the overall performance of the proposed scheme using multiple key performance indicators including the prediction accuracy, probability of handover failure, load balancing index and average network throughput.

To evaluate the performance of proposed mobility prediction model, we consider the prediction accuracy as the metric. The prediction accuracy denotes the ratio between the number of proper predictions and the number of all attempts predictions. Fig.4 shows the prediction accuracy at different times of the day. One can find that the prediction for night is more accurate than that for daytime. The reason is that users' location at night is more regular, in the dormitory or at home. From Fig.4, one

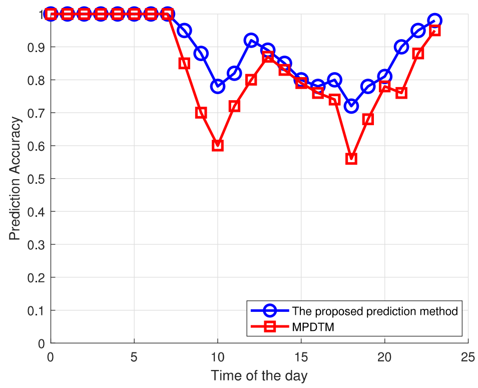

Fig. 4. Accuracy of predication between the proposed and the conventional methods

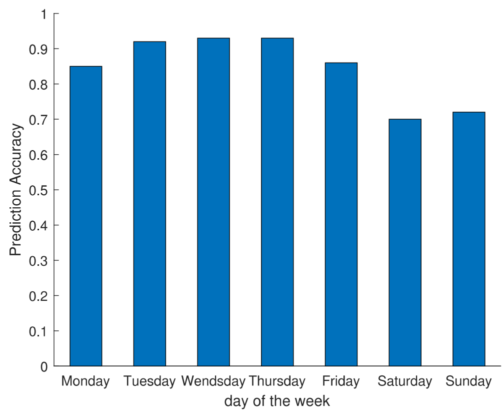

Fig. 5. Accuracy of one week

can find that the prediction accuracy of the proposed method is better than that of [10]. This is because the users' locations are highly correlated with their behavior, and the locations frequently visited by users have weekly regularity. However, the method in [10] do not consider the above factor. One can find an interesting trend in Fig.5, the prediction accuracy on Working days is higher than those on Saturdays/Sundays, Since on working days, the users' behavior is more regular and predicatable than those on weekends.

It can be seen from Fig.6, Fig.7 and Fig.8, the proposed method achieves better performance than the existing method, that is, more even distribution of network load, lower handover failure probability and higher network throughput. As the accuracy of the proposed mobility prediction method is higher than that of the exiting method, the proposed method can perform forward-looking load balancing more efficiently. The current MLB can take into account the load change of cells in the future, which can effectively avoid the cell load fluctuation, so resources can be reserved more efficiently for coming users in advance. Thus, the distribution of network load will be more stable and even, thereby reducing the system's handover failure rate and ultimately increasing system throughput.

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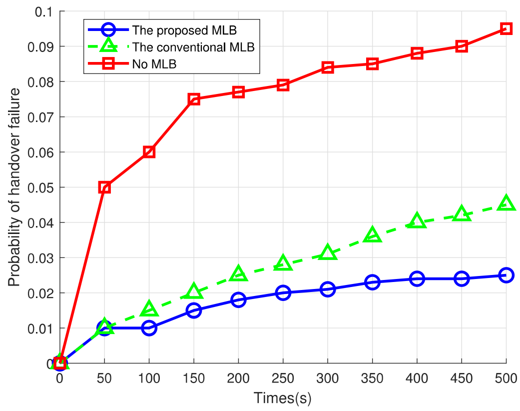

Fig. 6. Probability of handover failure

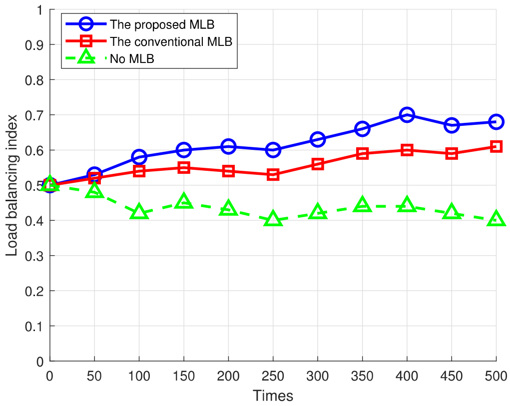

Fig. 7. Load balancing index

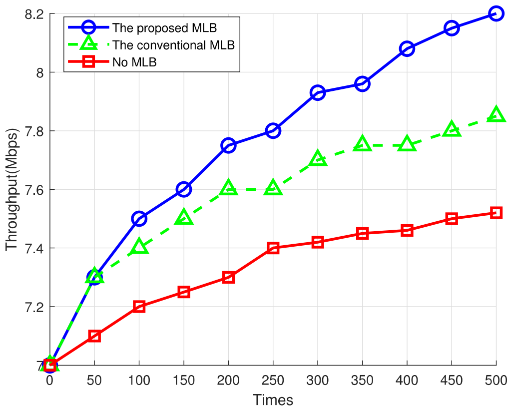

Fig. 8. Average network throughput

V. Conclusion

This article creatively proposes a novel and proactive load balancing scheme based on users' temporal and spatial prediction. The concept of soft load is put forward for the first time and it is regarded as one of the influencing factors in the current MLB. By adjusting the CIO, the load of overloaded cells is offloaded to multiple adjacent target cells. The simulation results show that the proposed method can better reduce the handover failure rate caused by user mobility and the fluctuation of network load. It can make the cell load distribution more uniform and the system throughput higher, thereby optimizing the network performance.

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