Proactive Load Balancing in Heterogeneous Cellular Networks

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Abstract
Recent exponential growth of data over cellular networks has cause the progression from conventional mobile communication networks to heterogeneous cellular networks (HetNets). Quality of experience (QoE)-aware traffic load balancing in such dense HetNets is considered a major problem. Current HetNets exploit reactive load balancing schemes that hinder in achieving desired QoE gain. In this paper, we propose a novel proactive load balancing framework which leverages content caching and mobility prediction to improve user QoE. We use Semi-Markov model to predict users’ future cells and a novel proactive caching algorithm is proposed to pre-fetch user future demands at these cells. This allows us to reduce cell congestion and offers better average downlink rates. To validate the effectiveness of the proposed framework, system level simulations are performed and compared with state of the art approaches. Encouragingly, our system achieves up-to 98.7% cell load balancing in terms of Jain’s fairness index, reduces 20% backhaul load, and provides 31% improved downlink rates at congested cells in contrast to reactive approaches.

1 Introduction
The recent exponential rise in the mobile data traffic has prompted the call for the evolution of cellular networks to provide top-notch quality of experience (QoE) with ultra-low latency and unprecedented capacity gain. The prodigious capacity gain in the future cellular networks is expected to come from network densification with heterogeneous networks (HetNets) architecture through the deployment of many low-power small base stations (SBS) in addition to the conventional macro base station (MBS) [14]. It is not difficult to anticipate that such massive deployments of nodes will create enormous challenges in terms of complexity, load balancing (LB), resource allocation, mobility management, backhaul congestion, energy consumption etc. The ambitious QoE demand from data-hungry applications means that there is a crucial need to empower network with intelligence-driven self-organizing paradigms. This will enable the network to prognosticate the up-coming problems earlier i.e., proactive operation mode. This level of proactivity can be achieved by inferring the user entity (UE) behavior and predicting future network states by exploiting the network historical information such as cell loads, user mobility patterns, content popularity, demand profiling etc. Proactive operation mode based self-organization can manage problems like cell resource allocation and overloading (congestion) actively, thus allowing mobile network operators to maximize users’ QoE.

HetNets traffic load balancing is a complex and open problem [2]. Notable key factors responsible for cell overloading include user mobility, content demands and base station (BS) transmission power. BS with high transmission power can offer high received signal strength indicator (RSSI), thus attracting UEs than neighboring low power BSs, resulting in uneven load distribution eventually. Furthermore, these congested cells have to accommodate incoming traffic in addition to current users with the certain level of QoE provisioning. Under such a scenario, the already congested cells will eventually become more over-loaded and hence can offer poor QoE to associated users. To overcome this load imbalance issue, content cache enabled low-power nodes have been proposed which fetch user content to balance cell loads and alleviate access-backhaul congestion [6,13].

Traffic offloading results in better QoE for all the UEs in the network in such a way that the offloaded UEs can get more physical resource blocks (PRB) from new BSs and remaining UEs at previously congested BS get relief from the congestion state and experience better downlink (DL) throughput. A simple solution for load balancing proposed by 3GPP, is cell individual offset (CIO) based offloading scheme known as cell-range expansion (CRE) that forcefully offload some UEs to neighboring BS [1] [22]. Only adding CIO affects signal to interference and noise ratio (SINR) of re-associated users adversely [3].

To-date, most of the existing work on cell load balancing solutions such as, [23][24][21][22] [11][19][16] operate in a reactive manner by triggering offloading procedure after any or some BSs becomes overloaded. This reactive initiation of
traffic offloading mechanism results in QoE degradation for all associated UEs because of packet loss and high latency at congested BS queue. Under the complex and massive base station deployment in HetNets, these rigid rule-based load balancing policies cannot meet the seamless connectivity objective of future cellular networks. To-date existing load balancing solutions fall short of mark for existing and future high rate and low latency operated applications such as virtual reality, high definition multimedia contents (4k video streaming), and time-critical machine-to-machine (M2M) processes, due to following notable limitations:

- Reactive traffic offloading i.e., operates after one or some of the cells become overloaded.
- Traffic offloading valid under stationary or low mobility conditions.
- Caching based traffic offloading schemes ignore user mobility information and existing caching schemes also fail to address important questions simultaneously “What, When and Where to cache?”.

To address above limitations, there is need to adopt a proactive load balancing solution for HetNets. For this, modeling of user mobility patterns (cell sojourn times) can predict user’s future destination cell and modeling of user content demands can predict expected future contents of the underlying user which can be accomplished by proactive caching. Therefore, mobility aware predictive content caching can be deemed as a suitable approach for proactive load balancing.

In this work, a proactive mobility load balancing framework for HetNets is proposed that takes account of user trajectories and traffic requirements together and caches the user’s expected contents proactively in the lightly loaded cells other than possibly congested cells. To best of authors’ knowledge, this is the first proactive load balancing solution that leverages user mobility patterns and content demands. Firstly, user trajectories are modeled through Semi Markov model to predict users’ future cell and secondly, for proactive content caching, users’ content demand profiling is modelled and solved as user-item based low-rank matrix approximation. Mobility and caching models together pre-fetch users’ expected contents at the lightly loaded cells. System simulations against state of the art load balancing schemes support the effectiveness of the proposed approach.

### 1.1 Contributions and Organization

Notable contributions of this paper are summarized as follows:

1. A novel proactive mobility load balancing framework is proposed to maximize user average downlink throughput and minimize cell loads. Framework leverages user mobility patterns and content demands jointly to fetch users’ expected contents in the lightly loaded cells other than possibly congested cells.

2. User content demand profile based proactive caching is modelled as low-rank matrix approximation and solved using matrix logdet optimization, while user mobility profiles are built using Semi-Markov model.

3. A real-time user-item movie rating dataset is used to validate the performance of proposed caching algorithm.

4. Performance of proposed load balancing framework is validated against start of the art load balancing schemes.

The rest of the paper is organized as follows. Section II presents the system model and problem formulation. Section III describes proactive load balancing framework. Section IV reports simulations and results. Finally, section V concludes the paper.

### 2 System Model And Problem Formulation

We consider a HetNets supervised by a central controller consisting of densely deployed of $B$ cells, $b = \{1, 2, ..., B\}$, with local cache. In this section, we first consider few assumptions before formulating the problem. Here, we have these following assumptions to support our model:

- We assume that downlink transmission rates are same for each user while passing by each cell.
- All users are continuously communicating with maximum downlink throughput rates.
- User sojourn times (stay at certain cell) within cells follow power law distribution as empirically determined in [24]. Fig. 1 shows a mobile user trajectory within voronoi cells. Referring to Fig. 1, $t_1, t_2, t_3, t_4$ represent user sojourn time within consecutive small cells along the user trajectory and they are identically and independently distributed.

- We consider only uni-directional user mobility. It is assumed that central controller has information of UE mobility and content demands. UEs are also enabled with limited cache memories. In our system, it is assumed that UEs distribution follow poisson point process (PPP). Before proceeding further, we define these entities: Firstly, let $\mathcal{U}$, $u = \{1, 2, ..., U\}$, represents the set of UEs in the system. $G$ and $W$ denote system bandwidth and bandwidth of a PRB respectively. $\mathcal{B}_b$, is the transmission power of BS $b$ and $h_{bu}$ is channel gain between BS $b$ and user $u$. System has a library of $F$ content files, which are indexed as $\mathbf{f} = \{f_1, f_2, ..., f_F\}$.
Each file is atomic and has size \( e_i \), file size vector is denoted as \( e = [e_1, e_2, ..., e_F] \in \mathbb{Z}^+ \). Backhaul link capacities between central controller and small cells are defined as \( v = [v_1, v_2, ..., v_B] \in \{0, \mathbb{Z}^+ \} \). Under the above system description, when a user \( u \) is associated with BS \( b \), its signal to interference and noise ratio (SINR) is defined as:

\[
\eta_{bu} = \frac{P_{b}H_{bu}}{\sum_{j \in B/b} P_{j}H_{ju} + \sigma^2}
\]

where \( \sigma^2 \) is noise power of each PRB for UE \( u \). For a given \( P_b \), the maximum achievable downlink rate per PRB from BS \( b \) is given by using Shannon capacity theorem:

\[
R_{bu} = W\log_2\left(1 + \frac{P_{b}H_{bu}}{\sum_{j \in B/b} P_{j}H_{ju} + \sigma^2}\right)
\]

where \( W \) is typically 180 kHz in an Orthogonal Frequency Division Multiple Access (OFDMA) based system and \( \sigma^2 \) is additive white Gaussian noise (AWGN) at UE from channel gain. In our system model we have \( B \) cells such that \( b \in B \). Therefore, if UE \( u \) is connected to BS \( b \) then association indicator, \( x_{bu} \) will be 1 otherwise 0. Moreover, load of the cell \( b \) is defined as \( y_{bu} = \frac{\delta}{R_{bu}} \), where \( \delta \) is user practical rate and \( R_{bu} \) is maximum achievable rate according to (2). Now, at time \( t \), utilizing \( x_{bu} \) and \( y_{bu} \) of all active UEs, load of the cell \( b \) is expressed as:

\[
l_p(t) = \sum_{b \in B} x_{bu} y_{bu} \quad \forall b \in B
\]

The term \( l_p(t) \) represents number of active users in cell \( b \) at time \( t \). Similarly, at time \( t \) system load vector is given as:

\[
L(t) = [l_1, l_2, ..., l_B]
\]

Practically, the available downlink capacity offered by a cell is equally shared among associated users, therefore perceived effective DL rate not only depends upon channel conditions (interference, path-loss etc) but also depends on current cell load (22). Therefore, Perceived DL rate can be normalized with cell load, and can be expressed as:

\[
r_{bu} = \frac{R_{bu}}{l_p(t)} \quad (4)
\]

Let the vector \( s = [s_1, s_2, ..., s_B] \in \{0, \mathbb{Z}^+ \} \) denotes cell storage capacities, thus they can deliver information coming from the central controller to associated UEs over wireless links with following rates:

\[
R = \begin{bmatrix}
R_1 & \cdots & R_{1,U} \\
R_2 & \cdots & R_{2,U} \\
\vdots & \ddots & \vdots \\
R_B & \cdots & R_{B,U}
\end{bmatrix} \in \{0, \mathbb{Z}^+ \}^{B \times U}
\]

\[
2.1 \text{ Mobility Prediction Model}
\]

In the cellular network space mobile users exhibit spatial and temporal footprints. Spatial footprint includes physical location of user while temporal presence means user’s staying duration within certain cell area. A typical mobile user’s physical trajectory in spatially (voronoi cells) and temporally (sojourn time) is illustrated in the Fig.1. User \( u \) spends \( t_n \) time in the cell \( b \), then moves towards another cell and so on. User’s sojourn time along with its spatial presence comprises daily mobility pattern. User’s mobility patterns can provide important information to network such as user spends relatively large times in the home or work cells while less time at other cells, [24, 20, 9, 10]. Moreover, using real-time mobile users mobility data these studies empirically determined that mobile users mostly follow same daily routine routes while moving from home to work or from work to home with very little randomness in the trajectories.

In our model, central controller enabled with mobility management entity (MME) exploits user \( u \) trajectories to learn, track and predict mobility patterns over the time and constructs its mobility profile. Mobile user’s trajectory exhibits memory property [24] therefore, mobility profile for a user \( u \) is modeled using Semi-Markov renewal process as described in [22], within discrete state space \( b = \{1, 2, ..., B\} \), is denoted by \( \{X_b, T_b : n \geq 0\} \), where \( X_b, T_b \) and \( B \) represent the state of \( b \)th transition, the time of \( b \)th transition and total cells respectively. Each cell (MBS or SBS) represents the state of Semi-Markov process, and a handover from one cell to another cell is taken as state transition. We assumed that this model is time-homogeneous. Therefore, the probability of transition from \( i \)th to \( j \)th cell for the user \( u \) which already spent \( t \) time in the \( i \)th cell is defined as:

\[
\Phi_{i,j}(t) = Pr(X_{b+1} = j, T_{b+1} - T_b \leq t | X_b = i) = p_{i,j} \Theta_{i,j}(t)
\]

where

\[
p_{i,j} = \lim_{t \to \infty} \Theta_{i,j}(t) = Pr(X_{b+1} = j | X_b = i), p_{i,j} \in P_u
\]

and

\[
\Theta_{i,j}(t) = Pr(T_{b+1} - T_b \leq t | X_{b+1} = j, X_b = i)
\]

where \( p_{i,j} \) describes handover probability from \( i \)th to \( j \)th cell for each user \( u \), \( \Theta_{i,j}(t) \) defines the sojourn time distribution in \( i \)th cell when next cell is \( j \). For each user \( u \in U \) central controller constructs probability transition matrix \( P_u \) and sojourn time distribution matrix \( \Theta_u \), which are described as:

\[
P_u = \begin{bmatrix}
P_{1,1} & P_{1,2} & \cdots & P_{1,B} \\
P_{2,1} & P_{2,2} & \cdots & P_{2,B} \\
\vdots & \vdots & \ddots & \vdots \\
P_{B,1} & P_{B,2} & \cdots & P_{B,B}
\end{bmatrix}
\]

\[
\Theta_u = \begin{bmatrix}
\theta_{1,1} & \theta_{1,2} & \cdots & \theta_{1,B} \\
\theta_{2,1} & \theta_{2,2} & \cdots & \theta_{2,B} \\
\vdots & \vdots & \ddots & \vdots \\
\theta_{B,1} & \theta_{B,2} & \cdots & \theta_{B,B}
\end{bmatrix}
\]

Exploiting the formulation given in [4], if we have past handover history (handover-time, cell-ID) of user \( u \), initialization of probability transition matrix \( P^{(u)} \) and sojourn time distribution matrix \( \Theta_u \), is given as:

\[
p_{i,j} = \frac{N_{i,j}}{N_i}
\]
\[ \theta_{i,j}(k) = \frac{N_{i,j,k}}{N_{i,j}} \]  

(12)

where \( N_{i,j} \) represents user \( u \)'s number of handovers from cell \( i \) to \( j \), \( N_{i,j} \) is the total number of handover from cell \( i \) for user \( u \) and \( N_{i,j,k} \) is number of handovers with sojourn time equal to or less than \( k \) from cell \( i \) to \( j \). Based on previous history of \( p_{i,j} \) and \( \theta_{i,j} \) for each user \( u \), after every \( t \) time steps, central controller generates (time, cell-ID) tuple i.e., \( \{T_{HO}, b_{NC}\} \) where \( T_{HO} \) is next handover time and \( b_{NC} \) is the future cell. Let for user \( u \), its current location at time \( t \) is given by \( b_u = (x_u, y_u) \), and future location coordinates \( b_{NC} = (x_{bNC}, y_{bNC}) \) using future location estimation algorithm defined in [8], we can estimate user \( u \)’s future location i.e.,

\[
t(t + t') = b_u(t) + \sqrt{(x_{bNC} - x_b)^2 + (y_{bNC} - y_b)^2} \ast t + \bar{v} \]  

(13)

where \( \bar{v} \) represents a unit vector originating from current coordinates to next most probable location coordinates and defined as:

\[
\bar{v} = \begin{bmatrix}
    y_{bNC} - y_b \\
    x_{bNC} - x_b
\end{bmatrix}
\]  

(14)

Finally, after estimating users’ future locations, at time \( t + t' \), for each \( u \), its cell association will be computed and user association matrix \( X \) will be updated and given as

\[
x_{bu} = \left\{ \forall u \in \mathcal{U} | b = \arg \max_{b \in \mathcal{U}} T_p/b_t \right\} \]  

(15)

\[
X(t + t') = \begin{bmatrix}
    x_{1,1} & \ldots & x_{1,U} \\
    x_{2,1} & \ldots & x_{2,U} \\
    \vdots & \ddots & \vdots \\
    x_{B,1} & \ldots & x_{B,U}
\end{bmatrix} \in \{0, 1\}^{B \times U} \]  

(16)

Where, [15] represents cell-load aware user-cell association. Now, exploiting the user-association information from matrix \( X \), if \( x_{bu} \) is future user-association, the estimated cell loads for time step \( t + t' \), are given as:

\[
l_b(t + t') = \sum_{b \in B} x_{bu} y_{bu} \]  

(17)

Using estimated cell loads for next \( t + t' \) interval, we can define which a cell will be congested or lightly loaded, therefore we have:

\[
\mathfrak{b}_{t'} = \begin{cases} 
    1, & l_b \geq L_{th} \\
    0, & l_b < L_{th}
\end{cases} \quad \forall b \in B
\]  

(18)

where \( L_{th} \) is the cell load threshold, \( L_{th} \in (0, 1) \), moreover \( L_{th} \) can be defined by operator based on QoE demand level from the users such as minimum downlink rate must be greater than \( \beta \) Kbps etc. Also, \( \mathfrak{b} \) is vector of lightly-loaded and congested cells with \((0, 1)\) entries, given as \( \mathfrak{b} = [\mathfrak{b}_1, \mathfrak{b}_2, \ldots, \mathfrak{b}_B] \). Therefore, at time \( t \), central controller is able to predict cell load conditions for \( t + t' \) time using (17), this information will be used to prepare lightly loaded cells to reduce congestion at fully loaded cells using proactive content caching. From central controller each cell gets a vector \( \bar{u}_b \) which contains the IDs of UEs moving from \( b \) lightly loaded cell at time \( t \) and will be at congested cell \( b_{NC} \) at time \( t + t' \), which is given by:

\[
\bar{u}_b = \begin{cases}
    1, & \text{user's next cell is congested} \\
    0, & \text{otherwise}
\end{cases} \quad \forall u \in U
\]  

(19)

2.2 Caching Model

Central controller exploits user-file request information to construct its content demand profile matrix \( D \). User \( u \) can request a content item \( f \) which might be a social network update (Facebook and Twitter), a sound file (as in Soundcloud), a movie (from Youtube) or News update (as in BBC or CNN), etc. Central controller keeps the track of user demands and rates these items according to the number of times a particular file is demanded (such as the most demanded file will be rated maximum value while least demanded or not demanded file will be rated minimum or zero). There exist \( U \) users and \( F \) files at central controller, thus matrix \( D \) can be stated as:

\[
D = \begin{bmatrix}
    D_1 \\
    D_2 \\
    \vdots \\
    D_U
\end{bmatrix} = \begin{bmatrix}
    d_{1,1} & \ldots & d_{1,F} \\
    d_{2,1} & \ldots & d_{2,F} \\
    \vdots & \ddots & \vdots \\
    d_{U,1} & \ldots & d_{U,F}
\end{bmatrix} \in \{0, \mathbb{Z}_+\}^{U \times F}
\]  

(20)

Practically \( F \gg U \), as every user cannot ask each file from the library \( f \), therefore central controller can rate only those files which are ever demanded by a user. Thus, matrix \( D \) will be a sparse matrix with large number of zeros. To cache user future demands, there is need to estimate full demand matrix, which is denoted as \( \hat{D} \). Without loss of generality, we assume that each user has already spent some time in the system and requested some files from the network, therefore central controller can construct its demand profile. Moreover, it is supposed that \( \hat{D} \) matrix will be a low-rank matrix. Finally, central controller formulates an optimization problem, to learn the relationship between a user and its demanded files in order to rate non-rated entries in the \( D \) matrix, which is given below:

\[
\min_{\bar{D}} \logdet((\bar{D}^T \bar{D})^{1/2} + I) \quad \text{s.t.:} \quad \bar{D}_{uf} = D_{uf}, \quad (u, f) \in \bar{u}
\]  

(21)

where \( \bar{u} \) is set of observed entries and \( I \) is identity matrix. Moreover, function \( \logdet \) is tighter rank approximation than nuclear norm and is defined \( \logdet((\bar{D}^T \bar{D})^{1/2} + I) \leq \|\bar{D}\|_F \). Above mentioned problem can be solved using different algorithms such as nuclear norm minimization solution [13], or through least-square minimization [7]. But an efficient algorithm, defined in [12] is exploited to learn missing user-file rating in the original matrix \( D \). Thus, learned user-item demand matrix is given by
\[
\tilde{D} = \begin{bmatrix}
\tilde{D}_1 \\
\tilde{D}_2 \\
\vdots
\end{bmatrix}
\begin{bmatrix}
\tilde{d}_{1,1} & \ldots & \tilde{d}_{1,F} \\
\tilde{d}_{2,1} & \ldots & \tilde{d}_{2,F} \\
\vdots & \vdots & \vdots \\
\tilde{d}_{U,1} & \ldots & \tilde{d}_{U,F}
\end{bmatrix} \in \{0, 1\}^{U \times F}
\]

Our ultimate objective is to cache future demands of those users which are currently in lightly loaded cells at time \( t \) but their next cell at time \( t + t' \) is a congested cell. Therefore we can proactively cache expected top most demand files, \( Top - N \) files represented by \( n \in \lambda = 1, 2, ..., N \) from these users, by sorting \( \tilde{D} \) files based on their rating in the decreasing order. Central controller can transfer these \( Top - N \) files to lightly loaded cells using heuristic algorithm mentioned in [5], the factor \( N \) depends on the cell storage capacity \( s_b \). Now, at each lightly loaded cell, there will be caching decision matrix \( C_b \), which contains these \( Top - N \) files for each user;

\[
C_b = \begin{bmatrix}
C_1 \\
C_2 \\
\vdots \\
C_U
\end{bmatrix}
\begin{bmatrix}
c_{1,1} & \ldots & c_{1,F} \\
c_{2,1} & \ldots & c_{2,F} \\
\vdots & \vdots & \vdots \\
c_{U,1} & \ldots & c_{U,F}
\end{bmatrix} \in \{0, 1\}^{U \times F}
\]

where \( c_{u,f} = 1 \) means the file \( f \) is cached for the user \( u \).

3 Proactive Load Balancing Framework

User mobility profile helps central controller to determine most probable future cell and load status of cells at time \( t + t' \), while user file demand profiling helps central controller to fetch user’s expected most demanding files at light cell at time \( t \). Therefore, using mobility and proactively caching jointly we can optimize cell loads by caching users future contents in the lightly loaded cells, if their next destination is a congested cell. Fig. 2 shows proactive load balancing framework with 5 cells. Central controller contains a binary vector \( \Theta \) to represent the load of lightly loaded cells and congested cells. From Fig. 2, cell 5 (red colored) is congested while cell 1 (blue colored) is lightly loaded, a UE is moving from cell 1 to 5. Central controller can estimate user \( u \) future location using [13] and predict that user will be at cell 5 after time \( t + t' \). Therefore, at time \( t \) cell 1 can pre-fetch future contents of \( u \) from central controller and transfer into local cache of \( u \) before leaving the current cell.

Hereafter, \( C_b \) files at lightly loaded cells needs to be transferred to users before they leave current cell \( b \), therefore files delivery time is bounded by user sojourn time \( \theta_{b,NC}(t) \) (start of sojourn time, \( t_{so1} \) and end of sojourn \( t_{so2} \)) in addition to achievable downlink rate, \( R_b \). Let suppose we have complete expected data of user \( u, \lambda_u \subseteq \tilde{D} \) at time \( t \) which he/she will be demanding at \( t + t' \) time, user requests for demanding files will be satisfied if following criteria holds

\[
\zeta_u(\lambda_u) = \frac{1}{N} \sum_{n \in \lambda_u} 1 \left\{ \frac{e_n}{t_{so2} - t_{so1}} \geq r_{b,u} \right\}
\]

where \( e_n \) is length of \( n \)th file and \( 1 \) is indicator function which returns 1 if statement holds else 0. An optimization problem can be formulated in order to maximize the file satisfaction ratio \( \zeta_u \) at cell \( b \) for each user \( u \), which is given by

\[
\begin{aligned}
\max_{\Omega_{b,NC} \cap r_{b,u}} \zeta_u(\lambda_u) &= \frac{1}{N} \sum_{n \in \lambda_u} 1 \left\{ \frac{e_n}{t_{so2} - t_{so1}} \geq r_{b,u} \right\} \\
\text{subject to:} \quad o &\leq \sigma^\max, \\
\quad r_{b,u} &\leq R^\max,
\end{aligned}
\]

where \( \sigma^\max \) is capacity constraints of user storage space and \( R^\max \) maximum practically achievable downlink rate from cell \( b \) to user \( u \).

Algorithm 1 shows the detailed procedure of proactive load balancing framework. Central controller builds demand profile matrix \( \tilde{D} \) for all users and future user association matrix \( \tilde{X} \), if next cell \( b_{CN} \) of user \( u \) is congested cell then central controller guides lightly loaded cells i.e., \( l_b \leq L_{sh} \) to cache future demand files of \( u \) and push to \( u \)’s local cache through solution of (23).

4 Simulations and Results

This section covers simulation evaluation of proposed proactive mobility load balancing (PLB) scheme. We compared proposed LB scheme with Max-RSRP and CIO-induced LB schemes in terms of cell loads, backhaul saving and UE downlink average rate (QoE).

4.1 Simulation Setup

We consider a HetNet consisting of MBS with 46 dBm transmit power and SBS with 30 dBm transmit power each. One small cell per sector of MBS. U UEs and SBS are uniformly placed. The distance dependent pathloss model is given by; \( PL(d) = 128.1 + 37.6\log_{10}(d) \) and \( PL(d) = 140.1 + 36.7\log_{10}(d) \) for MBS and SBS respectively, where \( d \) is distance between UE and BS in kilometers. Log-normal shadowing with standard deviation (STD) of 8dB and noise
Algorithm 1 Proactive Load Balancing Implementation

1: Input: \( \{T_{HO}, b_{NC}\}, U, B, L_{th} \)
2: for \( u \in U \) do
3: Future location, \( t(t + t') \) using (13)
4: end for
5: for \( b \in B \) do
6: New cell loads, \( l_b(t + t') \) using (17)
7: end for
8: Calculate \( \varpi \) using (18)
9: for \( b \in B \) do
10: Calculate \( \tilde{u}_b \) using (19)
11: end for
12: Estimate \( \hat{D} \) through solving optimization problem (21)
13: for \( u \in U \) do
14: \( \lambda_u \leftarrow \text{Top} - N \) files
15: end for
16: for \( b \in B \) do
17: Get caching matrix \( C_b \)
18: Solve Eq. (23)
19: Calculate \( l_b = \sum_{b \in B} s_{nu} \) by
20: end for
21: Output: Optimized cell loads \( L' \leftarrow [l_1, l_2, \ldots, l_B] \)

Figure 3. Cell association under Max-RSRP, CIO-enabled load balancing and proposed load balancing, blue triangle, red circles and black dots represents MBS, SBSs and UEs respectively, red lines (links) indicate user association with MBS cells while blue lines (links) show user association with small cells (a) Cell-UE association under Max-RSRP, (b) Cell-UE association under 10dB CIO induced load balancing and (c) Cell-UE association under proposed proactive load balancing framework.

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18: Solve Eq. (23)
19: Calculate \( l_b = \sum_{b \in B} s_{nu} \) by
20: end for
21: Output: Optimized cell loads \( L' \leftarrow [l_1, l_2, \ldots, l_B] \)

power spectral density of 174dBm/Hz is considered. System bandwidth 20MHz is used. The UE speed is chosen from the interval \( v_u = [1, 10] \) m/s. Users mobility traces are generated using power-law distribution with parameter \( \alpha = 3 \) and on average 9 handovers per user. For mobility in the 2D plane we used random walk model. To get user-file relation matrix, we used a real-time sparse dataset ML100K provided by MoivesLens which is publicly available±. UEs can request a files, from the the set of \( |F| = 1682 \) files. And, backhaul links capacity is \( v_b = 5 \) Mbps. Moreover, summary of the simulation parameters are listed in the Table 1. Additionally, UEs mobility trances are generated through random walk model. Simulations follows 500 Monte Carlo runs.

4.2 Simulation Results

Here we present a comparative analysis of proposed load balancing scheme with Max-RSRP and CIO-Induced LB scheme using comprehensive simulations. Performance sensitivity is analyzed by varying amount of UEs in the system. Also discuss effectiveness of proposed scheme over comparative schemes.

Cell Association, Load Balancing And Fairness: Fig 3 shows cell association under Max-RSRP, 10dB CIO enabled CIO based LB and proposed proactive LB. It can be observed from Fig 3(a), large number of UEs are connected with macro-cells while less number of UEs with small cells,
Table 1. SIMULATION PARAMETERS

| System Parameters                        | Value               |
|------------------------------------------|---------------------|
| Number of MBS                            | 1                   |
| Sectors per MBS                          | 3                   |
| SBS per MBS Sector                       | 1                   |
| Transmission Bandwidth                   | 20 MHz              |
| MBS Tx Power                             | 46 dBm              |
| SBS Tx Power                             | 30 dBm              |
| Cellular System Standard                 | LTE                 |
| MBS Height                               | 25 m                |
| SBS Height                               | 10 m                |
| No. of Users, U                          | 200                 |
| Mobility Model                           | Random Walk         |
| File Library size, |1682 |

Figure 4. Cell loads under Max-RSRP, CIO-enabled LB and proposed proactive LB

on the other hand, from Fig 4(b) small cells are more loaded than macro-cells. Under proposed scheme a balanced cell association is evident from the Fig 4(c). Caching algorithm proactively caches user demands in the light cells before they reached congested cells, thus loads of congested cells are reduced. Fig 4 shows cell loads Max-RSRP, CIO-based LB and proposed LB. It is clear that UE load is uneven under Max-RSRP and CIO-enabled LB, but nearly balancing number of UEs under proactive LB due to UEs profiling and data offloading at light cells rather than congested cells. Therefore, proposed scheme not only offers load balancing but also creates smart capacity for upcoming traffic. In order to measure cellular system load we adopted Jain’s fairness index [15]. Jain’s fairness index has been used in many studied such as [22, 21], to determine the fairness level among cell loads as load balancing indicator and therefore, it is described as follows:

\[ \sigma = \frac{\left( \sum_{b \in B} l_b \right)^2}{\left| B \right| \sum_{b \in B} l_b^2} \]  \hfill (24)

where \(|B|\) is number of BS and \(l_b\) is load of BS \(b\). Jain’s fairness index ranges \(\sigma = [0, 1]\), near to 1 means more fairness and vice versa. Fairness index \(\zeta\) for Max-RSRP, CIO-enabled and proactive LB are 84.3, 91.05, and 98.7 respectively, which support our fairness load balancing argument under proposed load balancing scheme.

User Quality of Experience Gain: UEs coming to congested cell, already have future contents in their cache therefore no longer bandwidth of congested cells is further reduced and all UEs at congested cells can have better DL rates eventually. Lighter cells successfully provided users future contents before they are leaving for congested cells using Algorithm 2, thus congested cell loads are shared with lightly loaded cells. On average there is a better downlink rate for every UE in the system. Average downlink rate for Max-RSRP, CIO-enabled and proactive LB are \(5.04 \times 10^4\), \(5.96 \times 10^4\) and \(6.8 \times 10^4\) bps respectively. Fig 5 shows average downlink rate under Max-RSRP, CIO-enabled and proactive LB. About 20%, 24.2% and 31.5% users can enjoy rates more than \(1.01 \times 10^4\) bps under Max-RSRP, CIO-enabled and proactive LB respectively. It is evident that clearly downlink rate per user is improved under proposed scheme.

Average Backhaul Saved in the System: Exploiting proposed novel caching algorithm for proactive load balancing, we saved significant amount of backhaul load through proactively offloading of UEs. We extended our experiment to observe average backhaul load saving through varying number of active users in the system. Table 2 shows simulation results through different different cell loads and backhaul saving. It is clearly evident form the Table 2 we saved about 20% average backhaul in the system.

5 Conclusion
In this work, a proactive load balancing framework is proposed exploiting user content demand profiling and mobility patterns jointly in order to reserve network resources in ad-
vance during the congestion. For this, user trajectories are modeled through Semi Markov model to predict users’ future cell and for proactive content caching, users’ content demand profiling is modelled and solved as user-item based low-rank matrix approximation. Proactive load balancing model pre-fetch users expected contents at the lightly loaded cells other than possibly congested cells. Evaluation results show that proposed framework outperforms as compared to reactive approaches in terms of load fairness, backhaul load reduction and downlink rate maximization. Therefore, on the average, 20% backhaul load is reduced at congested cells with 31% users are able to enjoy more higher downlink on the average, 20% backhaul load is reduced at congested cells other than possibly congested cells. Evaluation results show that proposed framework outperforms as compared to reactive approaches in terms of load fairness, backhaul load reduction and downlink rate maximization. Therefore, on the average, 20% backhaul load is reduced at congested cells with 31% users are able to enjoy more higher downlink.

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