Mobility Context Awareness to Improve Quality of Experience in Traffic Dense Cellular Networks

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***Abstract*—Mobile communication is one of the most ubiquitously used technologies in contemporary world, evolving towards its fifth generation (5G). The data traffic demand by moving users (vehicular users) has been constantly increasing. It is a key challenge in 5G to satiate the requirements of such moving users and provide good Quality of Experience (QoE), despite high mobility and traffic demand. In day-to-day life, there are several practical instances where cellular network is subjected to high load situation due to vehicular users. Groups of mobile users travel together (e.g. public transport) forming a moving network and pose congestion to cells they enter. Further, density of vehicular users change dynamically in a cell and at certain sites (e.g. signal lights), traffic jams arise frequently. Such scenarios would pose high load situation to respective serving base station. As a consequence, the cell site would experience high dropping and blocking of users and subject them to poor QoE. This work emphasizes on building mobility context awareness to alleviate such situations in traffic dense cellular networks. The strategies to predict user-cell transition are discussed and an algorithm to predict severity of vehicular user traffic is designed. Based on these mobility context information, suitable radio resource management (RRM), namely mobility load balancing and small cell activation/deactivation are pro-actively triggered. The simulation results exhibit substantial reductions in dropping and blocking of users, demonstrating improved QoE of users, despite high mobility and data demand.**

***Index Terms*- Context awareness, moving networks, RRM, vehicular user, traffic jams**

I. Introduction

Mobile communication is one of the key technologies in today's world with ever increasing number of mobile subscriptions [1], and on the verge of its fifth generation (5G). Due to the popularity of mobile multimedia services, there is a drastic increase in data traffic demand of mobile users [2]. Further, the number of connected devices has been growing exponentially and it is anticipated to reach the figure of 50 billion by the year 2020 [1]. At this pace, by year 2020 number of connected devices is anticipated to be $10-100$ times more than the present and traffic volume would be 1000 times larger. Thus, 5G mobile communications face key challenges of satiating high data traffic volume and accommodating higher number of connected devices in the network, with good QoE [2].

In real world scenarios, mobile users traveling in vehicles avail cellular broadband services (e.g. infotainment in car). Large number of mobile users would travel in a group (e.g. public transport) posing a high load situation in cells they enter. When several such users traveling in group are managed by a locally present access point, they form a moving network, which is foreseen to be widespread in near future.

Further, at certain sites (e.g. signal post), traffic jams are more frequent. In such sites, large number of vehicular users make momentary halt, giving rise to high load situation at serving base station. The resulting congestion due to these practical problems lead to dropping of several already connected users in cell and blocking of access attempts made by newly entered users to cell. These factors will negatively impact QoE of users in such cell.

Many schemes are present in literature to combat high load situation arising from congestion, such as coverage adaption, channel borrowing [3], mobility load balancing [5], heterogeneous access management [4] etc. But these schemes are required to be proactively triggered based on knowledge of traffic severity, in order to achieve efficient performance. Moreover, there are certain works in literature to detect hotspot situation in a cell [6][7]. Majority of these works consider high user arrival rate, low departure rate, or increased bandwidth demand of existing users causing hotspot situation in a cell. Further, blocking/dropping rates and network load figures are investigated to evaluate congestion status in a cell. However, these solutions do not rely on context information (e.g. moving network arrival, traffic jams etc.), to initiate suitable RRM strategies well in advance. Context awareness and supporting framework [8][9] are thus required to tackle aforementioned high load situations.

In addition to this, there are various methods to predict urban traffic jams based on feedback from large historic traffic data and a large number of trajectory tracking devices, traffic sensors [10], based on 2D cellular automata model [11], based on fuzzy search theory [12] and few based on video surveillance systems [13][14]. The above schemes are typically used to predict general traffic congestion, associated delays and convey these information to transport systems. However, these schemes are costly in terms of computation and infrastructure and are not necessarily designed from a cellular network perspective. This renders the aforementioned solutions not suitable for usage in cellular networks.

This work emphasizes on building mobility context awareness to enable efficient design of radio resource management, with a motive to improve QoE of users even in highly congested situations (e.g. traffic jams) or high mobility (e.g. moving networks). A procedure to predict user-cell transition is presented and used pro-actively to initiate load balancing (LB), in context of data intense moving networks. Further, a framework is proposed to predict vehicular traffic status from cellular network perspective. This a-priori context information about traffic jam formation is utilized to proactively initiate load balancing at the serving base station or activate/deactivate small cell at anticipated site of frequent traffic jams.

The remainder of this paper is organized as follows: Section II deals with prediction of user-cell transition in context of moving networks and its evaluation. Section III discusses traffic status prediction and respective evaluation, and Section IV provides a conclusion and indicates future work.

II. Context aware RRM for moving networks

As discussed in section I, data intense moving networks pose a practical problem of high load situation, in any cell it would enter. In order to combat such situation, user-cell transition prediction could be used. If next cell for transition of moving network is known, then suitable RRM (e.g. load balancing) could be initiated at predicted site to release/reserve resources, in advance. Fig.1 illustrates the aforementioned scenario. There are several schemes in literature to predict future cells of a user based on machine learning [15], route clustering [16] and other history based schemes [17][18]. However, such schemes have high computational complexity and cost. Hence, cell transition prediction based on simple real-time geometry measurements is presented in this work, taking into account directive mobility of moving networks.

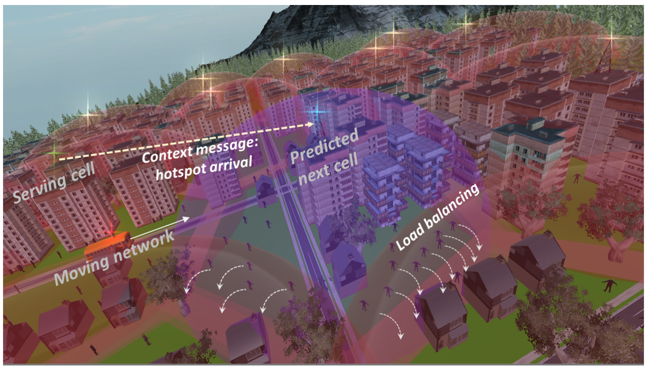

Fig. 1. Context aware LB to accommodate moving networks

A. Prediction of user-cell transition

In this section, a scheme to predict user-cell transition based on user geometry (dB) is proposed, which will assist in designing proactive LB for data intense moving networks. Typically, vehicular users in real world follow direction based mobility [19] [20] as opposed to random waypoint mobility (RWP) as depicted in Fig. 2.

The proposed scheme considers geometry of the user with respect to neighboring cells. Geometry is defined as the average carrier to interference ratio and is given by,

$$Geometry\,(dB) = 10log_{10}\left(\frac{P_k}{\sum_{i=1,i\neq k}^{n} P_i}\right) \qquad (1)$$

where P_k is the power received from considered base station and P_i are the interference from other base stations.

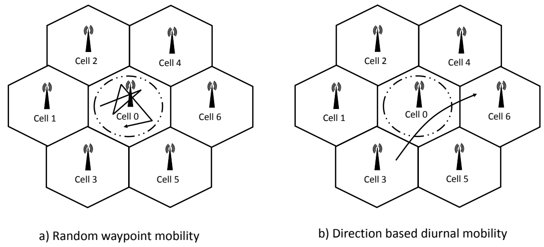

Fig. 2. RWP mobility and Direction based diurnal mobility

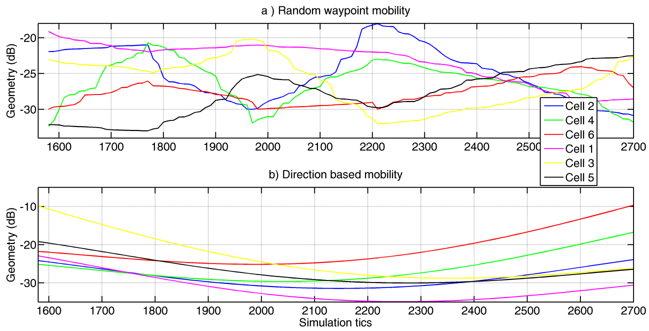

Fig. 3. Exemplary geometry patterns

In Fig. 2.a), the trajectory of a user that follows random waypoint mobility is depicted. If geometry of such a user with respect to its neighboring cells are recorded, then obtained geometry pattern is as shown in Fig. 3a). The geometry pattern for random waypoint mobility is obscure and non trivial for purpose of cell transition prediction. However, if we consider a real world user with direction based diurnal mobility (e.g. commuter in public transport) as depicted in Fig. 2.b) and record its geometry with respect to neighboring cells, then geometry pattern is as shown in Fig. 3b). The geometry pattern exhibits a positive gradient for cells which are being approached (cell 6, cell 4, cell 2), whereas geometry pattern has a negative gradient for cells from which the user is moving away (cell 5, cell 3, cell 1). This behavior can be utilized for prediction of next cell for user transition.

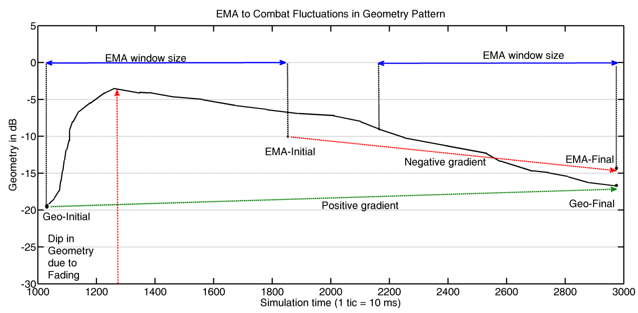

Fig. 4. EMA to combat fluctuations in geometry pattern

The geometry values are influenced by characteristics of wireless channel such as shadowing, fast-fading etc. As a result, there might be fluctuations in geometry pattern. These fluctuations can potentially impact the prediction of next cell. Consider an extreme case as in Fig. 4, which shows the geometry pattern with respect to a cell from which the user is moving away. The initial recordings of geometry pattern suffer due to fading which is reflected as large dip in geometry values. If we consider instantaneous initial value (Geo-Initial) and instantaneous final value (Geo-Final) to determine the gradient, then a positive gradient is obtained in extreme cases. This would wrongly infer that the cell is being approached.

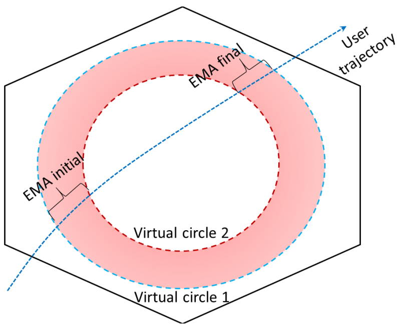

Fig. 5. Recording of samples to calculate EMA

In order to combat such extreme situations, exponential moving average filtering (EMA) could be used instead of instantaneous values. EMA applies weighting factors which decrease exponentially, so that the most recent values get higher weightage than the older values [21]. To obtain EMA, a setup as shown in Fig. 5 is used. There are two virtual circles inscribed in a cell, corresponding to two different signal strength thresholds. User geometry samples recorded in the region between these circles is used to calculate EMA. If EMA is used (EMA-Initial, EMA-Final) instead of instantaneous values as in Fig. 4, a negative gradient is obtained as desired, inferring that user is moving away from the cell. Even though occurrence of such an extreme case is rare, it is preferable to use EMA as precaution.

The set of potential next cells are determined dynamically based on the geometry patterns which have positive gradient. The probability of transition into these next cells based on geometry values are given by:

$$p_1 = \frac{EMA_{geo1}}{EMA_{geo1} + EMA_{geo2} + EMA_{geo3}} \tag{2}$$

$$p_2 = \frac{EMA_{geo2}}{EMA_{geo1} + EMA_{geo2} + EMA_{geo3}} \tag{3}$$

$$p_3 = \frac{EMA_{geo3}}{EMA_{geo1} + EMA_{geo2} + EMA_{geo3}} \tag{4}$$

where EMA_{geo1}, EMA_{geo2} and EMA_{geo3} are the EMA of geometry values of potential next cells. These are obtained by performing EMA [21] on geometry values recorded in the region between two virtual circles, before user leaves present cell (same as EMA-Final).

B. Evaluation

A LTE system level simulator is used to set up a multi-cell scenario as shown in Fig. 6. Each cell has base station in its center and has several static background users in it. Evaluation methodology follows [22] and simulation parameters are tabulated in table I. A data intense moving network travels through the cells as depicted in Fig. 6. Table II summarizes prediction of moving network transition into potential next cells. It could be seen that, cell transition is predicted with high accuracy.

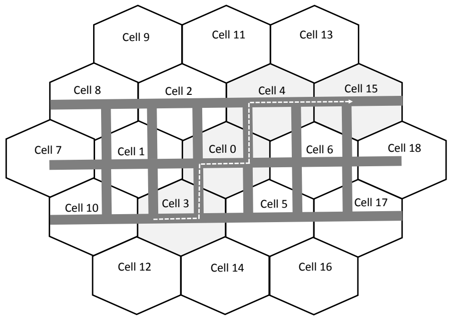

Fig. 6. User-cell transition

TABLE I
SIMULATION PARAMETERS

Parameter	Assumption
Carrier frequency	2 GHz
System bandwidth	10 MHz (50 PRBs)
Total transmit power	40 W($s2s = 500$m)
Control channel overhead	12%
Shadowing	log-normal Standard deviation: 8 dB Decorrelation distance: 50 m
Fast fading	2-tap Rayleigh fading channel
Noise power	-174 dBm/Hz + $10 \cdot \log_{10}(B) + 7$
Background users per cell	30
Users in Moving networks	60 at 80 km/h

TABLE II
USER-CELL TRANSITION PREDICTION

Present Cell	Next Cell 1	Next Cell 2	Next Cell 3	$P_{Nextcell1}$	$P_{Nextcell2}$	$P_{Nextcell3}$
Cell 3	Cell 0	Cell 5	Cell 1	0.786	0.0156	0.197
Cell 0	Cell 4	Cell 6	N/A	0.716	0.284	N/A
Cell 4	Cell 15	Cell 13	N/A	0.996	0.004	N/A

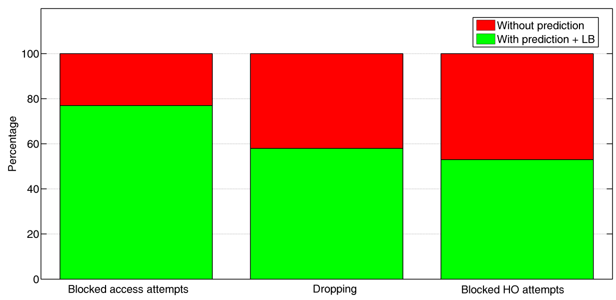

Fig. 7. Key performance indicators

As soon as the next cell for transition is predicted for data intense moving network, context aware LB is triggered in predicted cell. This procedure will free up resources and make it allocatable for moving networks. Fig. 7 depicts the average reductions in dropping of connected users ($\approx 42\%$), blocked access attempts ($\approx$ 23%) and blocked handover attempts ($\approx 47\%$), thus indicating improved QoE.

III. Context aware RRM in Traffic jams

When several vehicular users availing cellular broadband services are at halt during traffic jams, high load situation is posed to serving base station. In order to combat such problem, a framework is proposed in this section to predict traffic status in a cell. This context information is then used to activate/deactivate small cells suitably. An illustration of aforementioned concept is provided by Fig. 8.

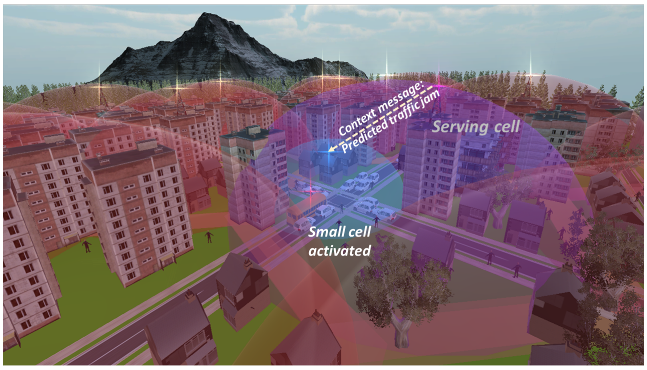

Fig. 8. Context aware RRM in traffic jams

A. System model

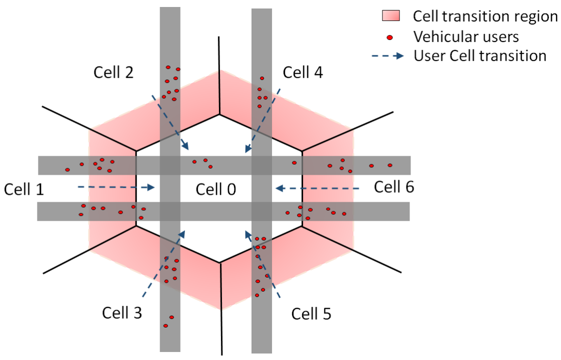

Fig. 9. Traffic jam formation model

Fig. 9 depicts the system model considered to monitor vehicular users traveling towards site of interest and obtain substantial statistics required to design traffic status prediction algorithm. Cell 0 is the site of interest where traffic jams occur frequently (due to presence of signal posts etc.). The mobility behavior of vehicular users in cells neighboring to this site are monitored and those that are traveling towards cell 0 are investigated. Such users are identified when Eq. 5 is satisfied.

$$\frac{\sqrt{(x_b - x_n(i))^2 + (y_b - y_n(i))^2}}{\sqrt{(x_b - x_n(i-1))^2 + (y_b - y_n(i-1))^2}} < \quad 1, \tag{5}$$

where, $(x_b,\ y_b)$ denotes position of base station (cell 0), $(x_n(i),\ y_n(i))$ is the present location of vehicular user n, and $(x_n(i-1),\ y_n(i-1))$ is its past position. Further, in the considered system model, a transition region is defined at boundaries of neighboring cells. A user is in transition region if Eq. 6 is satisfied:

$$g_s < \theta_t, \tag{6}$$

where g_s is the geometry (dB) experienced by user with respect to serving base station and θ_t is a threshold value used to set cell transition region, which is derived from radio propagation data.

The group of vehicular users satisfying Eq. 5 are monitored and below statistics are obtained to design algorithm to predict traffic severity at the site of interest (cell 0):

1) N_t $\rightarrow$ number of vehicular users in transition region of neighboring cells, having cell 0 as next cell for transition.
2) N_{Ct} $\rightarrow$ number of vehicular user clusters in transition region of neighboring cells, having cell 0 as predicted next cell.
3) N_0 $\rightarrow$ number of vehicular users already transited to cell 0 from neighboring cells.
4) T_t $\rightarrow$ total data traffic demand of vehicular users in transition region of neighboring cells.
5) $N_{\Delta vj}$ $\rightarrow$ number of vehicular users with negative velocity gradient, nearby frequent jam location.
6) $N_{C\Delta vj}$ $\rightarrow$ number of vehicular user clusters with negative velocity gradient, nearby frequent jam location.
7) $T_{\Delta vj}$ $\rightarrow$ cumulative data traffic demand of vehicular users with negative velocity gradient, nearby frequent jam location.

Note: Prediction of user-cell transition discussed in section II-A is used in obtaining N_t, N_{Ct} and N_0.

B. Vehicular cluster detection

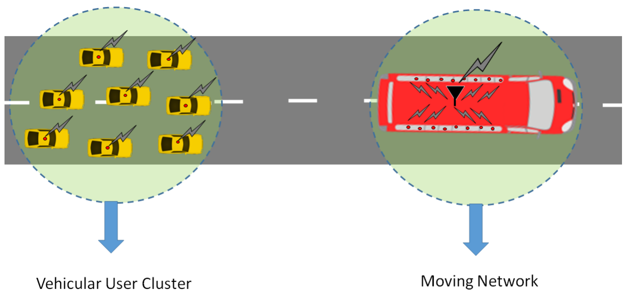

Fig. 10. Vehicular user cluster

During peak time of the day, several vehicular users travel in a group from various locations and at certain sites such as signal posts make a brief halt, giving rise to traffic jams. Thus, detection of such vehicular user clusters in and around the site of frequent traffic jam is a valuable indicator in prediction of traffic jams, which would arise in near future. Presence of vehicular user clusters is identified by following algorithm:

Data:

1) Positions of vehicular users in each neighboring cell satisfying Eq. 5.
2) Predefined values for cluster radius (R) and minimum number of vehicular users required to form a cluster (θ_{NR}).

Step 1:

Obtain distances among all vehicular users in each cell satisfying Eq. 5

for $i = 1$ to N
  for $j = 1$ to N
    if $i \neq j$ **then**
      obtain d_{ij}
    end if
  end for
end for

where, N is the number of vehicular users approaching, $i, j \in (1, 2, ..., N)$, d_{ij} is the distance between users i and j.

Step 2:

Find the maximum number of users N_R present in a radius R around user k, advancing in same direction.

$\forall$ k $\in (1, 2, ..., N)$, determine the k which satisfies Eq. 7 more number of times.

$$d_{kj} <= R \tag{7}$$

Step 3:

If Eq. 8 is satisfied, then a vehicular cluster exists.

$$N_R >= \theta_{NR}, \tag{8}$$

Algorithm 1: Vehicular cluster detection

C. Traffic jam prediction

Based on the collected statistics of vehicular user activity in and around the site of interest (in this case cell 0), traffic status prediction algorithm is designed. The vehicular users are assumed to request full buffer data traffic (the buffers of the users' data flows always have unlimited amount of data to transmit [22]), hence constituting a worst case scenario. The traffic status indicator (TSI) would assume one of the following states:

a) Green: There are not enough vehicular users, clusters or moving networks in cell 0 or in transition region of cells neighboring to it, to form a traffic jam or pose a congestion situation in near future. The cumulative data traffic demand and number of access attempts made by vehicular users to cell 0 are minimal and there is no indication of high load situation occurring soon. The statistics about data traffic demand are considered, because in certain cases even though there are not enough users present in traffic jam physically, cumulative data traffic demanded by them might be high enough to cause congestion. Eq. 9 defines the condition for TSI to be green:

$$\begin{aligned}(N_t < \theta_N) \wedge (N_{Ct} < \theta_{Ct}) \wedge (N_0 < \theta_0)\\ \wedge (T_t + T_{\Delta vj} < \theta_{T\Delta vj}),\end{aligned} \tag{9}$$

where $\wedge$ indicates the logical AND operation.

b) Yellow: This state indicates that high traffic situation is likely to happen in near future of the cell. Sufficient number of vehicular users/moving networks will already be in transition region expected to enter cell 0 or cumulative data traffic demand of vehicular users in transition zone is large enough to pose hotspot situation in cell 0 in the time coming. Eq. 10 denotes the condition for TSI to be yellow. Eq. 10 also investigates if the sum of vehicular users in transition region and those already moved to cell 0 are large enough to pose high load situation:

$$\begin{aligned}(N_t > \theta_N) \vee (N_{Ct} > \theta_{Ct})\\ \vee (N_t + N_0 > \theta_{N0}) \vee (T_t > \theta_{Tt}),\end{aligned} \tag{10}$$

where $\vee$ indicates the logical OR operation.

As soon as TSI is yellow, load balancing can be triggered proactively to free up resources. This enables cell 0 to accommodate soon to enter vehicular users, already in transition region. Fig. 11 depicts the process of load balancing (LB) used in this work, where static background users present in boundary of cell 0 are deliberately made to be served by appropriate neighboring base stations. Care should be taken that LB is not carried out on vehicular users, since their movement would lead to higher LB failures and ping-pong handovers.

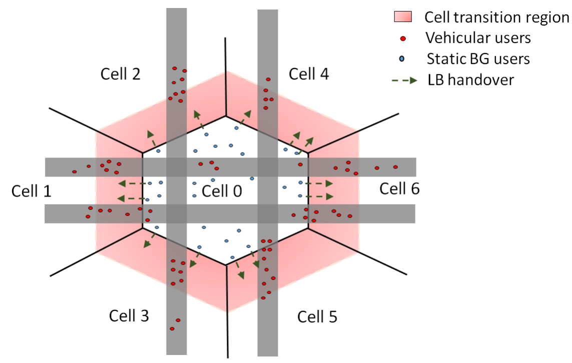

Fig. 11. Proactive load balancing

c) Red: If Eq. 11 is satisfied, then it indicates that traffic jam is imminent at the frequent jam site. The vehicles typically apply brakes and slow down when they are supposed to halt at signal posts. Eq. 11 makes use of such behavior and considers statistics of vehicular users/moving networks near jam site, with negative velocity gradient and their cumulative data traffic demand. To assist the attainment of these statistics, a predefined radius around anticipated jam site is used and vehicular users contained in it are investigated. Velocity estimation by Doppler processing [23] is assumed to be present in the considered system.

$$(N_{\Delta vj} > \theta_{\Delta vj}) \vee (N_{C\Delta vj} > \theta_{C\Delta vj}) \vee (T_{\Delta vj} > \theta_{T\Delta vj}). \quad (11)$$

The threshold values θ_N, θ_{Ct}, θ_0, $\theta_{T\Delta vj}$, θ_{N0}, θ_{Tt}, $\theta_{\Delta vj}$ and $\theta_{C\Delta vj}$ have to be set by the network operator on the basis of available resources at site of interest and maximum number of connections that could be served. The thresholds can be fine tuned by the operators suitably.

Once the TSI is red with respect to a frequent jam site (e.g. signal post), the nearest small cell to the site is activated. The vehicular users in traffic jam, which is bound to happen at the site, will now be served by the small cell (SC). Fig. 12 demonstrates the activation of SC at frequent traffic jam site. Further, as vehicular traffic jam disperses, TSI changes accordingly to yellow and then to green. Small cell is deactivated proactively to minimize energy consumption of small cells.

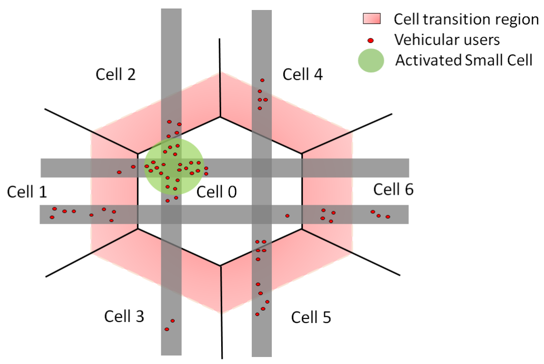

Fig. 12. Small cell activation

D. Evaluation

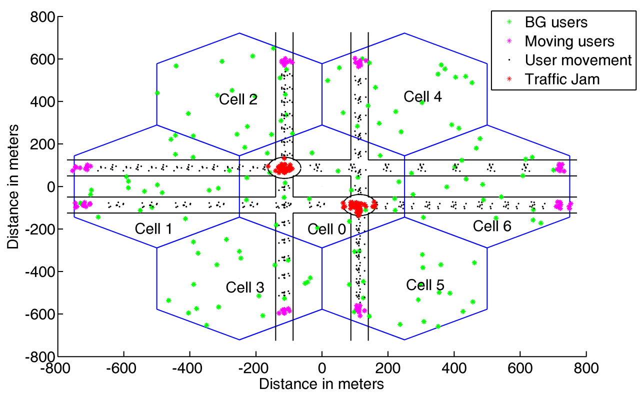

Fig. 13. Simulation of traffic jam formation

A multi-cell scenario is simulated as depicted in Fig. 13. Cell 0 is the site of interest with crossroads where traffic jams occur frequently. The vehicular users originate from neighboring cells and travel into cell 0 as per road topology, and cause traffic jams. Simulation parameters are same as described in section II-B table I. In addition, 135 vehicular users at velocities ranging from $30-80$ km/h are deployed. Few small cells with s2s of 250 m and transmit power of 10 W are also present. The thresholds are set as $\theta_N = 30$, $\theta_{Ct} = 3$, $\theta_0 = 45$, $\theta_{N0} = 45$, $\theta_{C\Delta vj} = 3$, $\theta_{\Delta vj} = 30$, $\theta_{T\Delta vj} = 250$ MB, $\theta_{Tt} = 250$ MB $\theta_{NR} = 5$ and $R = 30$ m. Monitoring interval is set as 1 s.

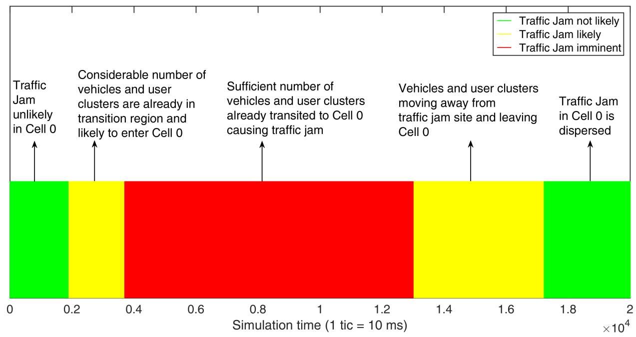

Fig. 14. Traffic status indicator

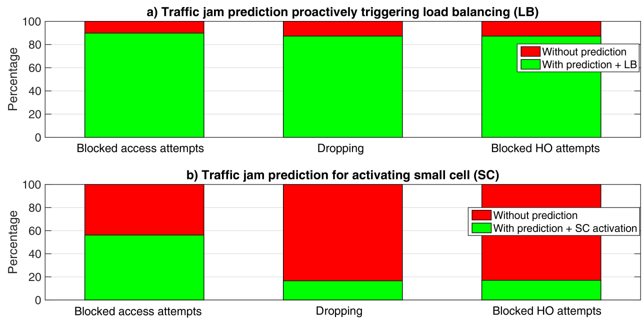

Fig. 15. Improvements in KPIs

Fig. 14 shows the evolution of TSI with simulation time. When TSI is yellow, load balancing is initiated proactively at the site of cell 0. (Note: LB initiated only once, when TSI changes from green to yellow) The static background users near cell boundary in cell 0 are load balanced. This context aware procedure frees up some resources for incoming vehicular users to cell 0 in near future. This procedure reduces dropping of users by $\approx 18\%$, blocking of new access attempts by $\approx 10\%$ and blocked handover attempts by $\approx 18\%$ (shown in Fig. 15 a)). Further, when TSI turns red, relevant small cells are activated to serve the vehicular users at respective traffic jams. In the presented evaluation, traffic jams occur almost simultaneously at two sites as depicted in Fig. 13. By the activation of small cells, dropping of users is reduced by $\approx 82\%$, blocked access attempts is reduced by $\approx 42\%$ and blocked handovers are reduced by $\approx 81\%$ (shown in Fig. 15 b)). The reduction of these KPIs, indicate that users have improved QoE even during traffic jams.

Further, when traffic jam disperses (TSI changes from red to

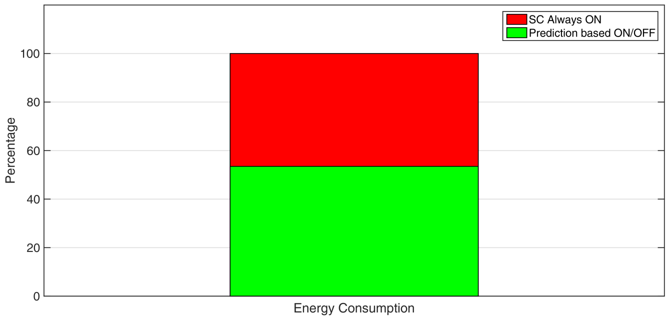

Fig. 16. Comparison of energy consumption

yellow), activated small cell is switched off. With prediction based scheme, energy consumption is reduced by $\approx$ 45% (Fig. 16) for considered simulation set up. Thus, prediction based small cell activation/deactivation not only improves user QoE but also is energy efficient compared to small cell being always ON.

IV. Conclusion and future work

Mobile communication has evolved through various generations and is now on the verge of its fifth generation (5G). Higher traffic volume (1000 times more) and larger number of connected devices ($10-100$ times more) are anticipated in 5G. Several practical problems arise in day-to-day situations due to vehicular users availing cellular broadband services. Large number of such vehicular users when controlled by a locally present access point, form a moving network. These entities are data intense and are envisioned to become widespread in near future. In addition, when large number of data demanding vehicular users are stuck in a traffic jam, high load situation is posed to serving cell. These problems lead to high dropping and blocking of users, thereby hindering QoE of users. This paper presented solutions to these problems by building mobility context awareness. A real-time geometry (dB) based user-cell transition method was used to design context aware LB to alleviate high load due to moving networks. Further, a framework to predict traffic jams was proposed from cellular network perspective. Context aware activation/deactivation of small cell was enabled to overcome respective high load situation. Evaluation of these schemes proved to reduce blocking of access attempts, dropping of connected users and blocking of handover attempts, thereby improving QoE. Future work is to tailor these presented solutions with other 5G concepts such as millimeter wave technology and beamforming, to provide mix of services in data dense networks.

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