Achievable Performance Gains Using Movement Prediction and Advanced 3D System Modeling

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***Abstract*—In contrast to synthetic user mobility models, user movements in real-world scenarios are restricted and typically conform to location-specific street layouts. Further in urban areas, user movements depend on traffic laws and behavior of other users. For example, vehicular users are said to stop at red traffic lights or should brake, if a vehicle ahead suddenly stops. Moreover, cellular users moving in these urban environments may face severe and abrupt changes in receive signal levels, which in the worst case result in connection drops. In order to pro-actively prevent these situations, where link rate decreases, handover execution is triggered too late, or even the connection dropped, a context-enhanced user movement prediction scheme is presented in this paper. Further, achievable performance gains using user movement prediction and modeling network deployment, user mobility, and radio propagation in a more realistic manner as envisioned for the next generation of wireless networks 5G are presented.**

I. Introduction

Exploiting context information on various aspects of people's every day life and particular environment has been in the focus of research [1] not only since numerous activities on data mining in social networks and web fora around the world started. In particular, the ability of an entity (e.g. wireless system, network management, access node, user terminal, service, application, etc.) to adapt to a specific context, which is also referred to as context awareness, is regarded as a key enabler for group management and content selection [2], group communications [3], as well as improved system, transport, and service adaptations [4], [5]. Moreover, the vision of transforming today's wireless systems into context aware networks and systems that are able to assist its users without their explicit interactivity [6] and their potential benefits highlight the significance of context awareness for future, intelligent ICT infrastructures.

For instance, enhanced mobility support and service provisioning are crucial for mobile network operators in order to mitigate OPEX and to stand out from their competitors. Further, a modular design approach allows for eased integration of modules tailored for specific applications and use cases, such as mobility support or network traffic management. For example, an increased amount of control signaling that possibly includes Authentication, Authorization, Accounting (AAA) processes (e.g. in case of vertical handovers), service interruption during handover (HO) execution, if soft handover is not supported, etc., may impose a burden on network capacity, negatively affect service latency, and degrade user's Quality of Service (QoS). For handling these issues, context-aware middleware approaches that aim at relieving the application logic from the burden of determining the most suitable air interface have been proposed [7], [8], and demonstrated to achieve accurate estimations of node mobility and to perform connection selection and establishment with very limited overhead. Moreover, the massive reduction in size and cost of electronic user equipment have further contributed to a reality where the majority of people carries along at least one wireless communication device, e.g. a smartphone. Modern user terminals dispose of a variety of sensors, wireless interfaces, and applications for supporting context aware services, ranging from everyday life tasks, such as location-related weather forecast, to enhanced mobility support across Radio Access Technologies (RATs). These technological and societal evolutions laid the foundation for researching meaningful opportunities for the exploitation of any kind of context information that is made available. In the scope of this paper, user, network, and environment context information is used for improving mobility support (e.g. connection drops and HO failures) and overall network performance in terms of throughput. In contrast to standard 2D and snap-shot based evaluation methodologies, realistic modeling of user mobility, including location, speed, direction, acceleration, as well as of 3D network deployment and radio propagation aspects [9] is used for evaluating achievable gains using user movement prediction.

The remainder of this paper is organized as follows: section II describes realistic system modeling aspects, HO event, and mobility-related Key Performance Indicators (KPIs), section III illustrates the applied user movement prediction scheme, section IV presents performance evaluation results, and section V concludes the paper.

II. Modeling Aspects

Typically, system-level performance is evaluated by averaging over a large number of scenario "snapshots". For each snapshot, users are randomly dropped into the considered service area. Statistics on individual user link performance are aggregated and cell- or system-level KPIs are determined, e.g. spectral efficiency in bit/s/Hz [10]. In analytical approaches [11], [12], user arrival times are modeled equivalent to session initiation times, and session durations as realizations of Poisson and exponentially distributed random processes, respectively. However, these models do not account for possible signal level degradations that occur due to user mobility or connection timeouts during HO processes due to induced delays. In this paper, user movements and thereby triggered HO processes are explicitly modeled and evaluated for the sake of more realistic system performance evaluations. Individual user movements and the physical environment users pass through have a direct impact on user link quality and thus throughput. Further, direction-oriented user mobility inevitably leads to HO processes that are triggered for handing over ongoing sessions from one Base Station (BS) to another. However, these HO processes do not occur instantaneously but induce some delay and thus potentially affect user-specific End-to-End (E2E) performance. The detailed modeling of user mobility and HO processes is particularly relevant for delay-sensitive services that are prone to performance degradation due to delays in data packet delivery. Hence, user mobility may severely affect E2E performance and needs to be considered for realistic system performance evaluation.

A. Modeling Deployment and User Mobility

Currently rolled out LTE networks are required to support a wide range of user velocities ranging from low and nomadic to even high speed mobility. Since changes in user mobility directly affect network performance, knowledge on mobility-related context (location, speed, direction, acceleration, etc.) may be beneficially exploited for enhancing system performance. For example in [13], user movement trajectories are predicted for triggering pro-active RRM and congestion avoidance. Since user traffic demands are expected to dramatically increase in the future [14], in particular in dense urban areas, a realistic 3D urban environment is considered. This environment model is closely aligned to the envisioned model for a *dense urban information society* as proposed by the METIS 5G project [9] and illustrated in Figure 1. The deployment consists

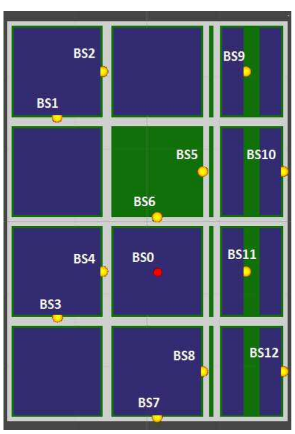

Fig. 1. Dense urban scenario [9]

of one LTE macro (BS 0) and several micro BSs (BS 1-12) operating at a carrier frequency of 2.6 GHz and using different transmit powers. At the macro BS 0, three sector antennas are deployed with one antenna steering into northern direction and the other antennas are oriented with 120 degrees offset with respect to north. Mirco BSs antennas are steered toward streets perpendicular to building walls. Further, vehicular users are assumed to move in the depicted street layout (cf. Figure 1).

B. Handover Event and KPIs

For intra-frequency mobility among deployed macro and micro cells, HO processes are triggered as soon as the condition for measurement reporting becomes true. The following simplified HO condition has to be satisfied for a certain amount of successive time instances, referred to as *time-to-trigger* (TTT), until HO process is triggered:

$$RSRP_t - RSRP_s > HOM(s,t), \tag{1}$$

where $RSRP_t$ and $RSRP_s$ denote the Reference Signal Received Power (RSRP) values and HOM refers to the overall HO Margin (HOM) with respect to *serving* BS s and *target* BS t. In general, HOM value settings have an impact on link availability during HOs, on the success rate of HOs, on the occurrence of unwanted ping-pong HOs, and on the load distribution between different cells. For assessing mobility support and in particular HO performance, several KPIs, such as *connection dropping ratio* (CDR) and *HO failure ratio* (HFR) are evaluated in this paper.

III. User Mobility and Prediction Schemes

In contrast to synthetic user mobility models, e.g. random walk [15], user movements in real-world scenarios are restricted and typically conform to location-specific street layouts. Further in urban areas, user movements depend on traffic laws and behavior of other users. For example, vehicular users are said to stop at red traffic lights or should brake, if a vehicle ahead suddenly stops.

Realistic street layouts of urban areas include crossroads at which users may choose to turn or continue moving into the same direction of travel. In [9], user behavior at crossroads is modeled by a random experiment that results in the state transitions and thus changes in user directions illustrated in Figure 2. However, the fact that users that are about to turn at

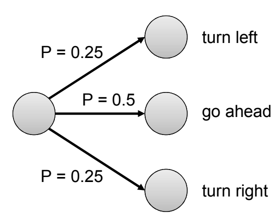

Fig. 2. State transition diagram [9]

the next crossroad usually slow down before making a turn is not taken into account. In order to model user behavior in a realistic manner and capture the effects of traffic laws, e.g. red light, on user movements and behavior of vehicular users approaching crossroads. Here, the velocity of users approaching a crossroad is decreased close to zero. The decision whether users will continue moving straight ahead or make a turn is based on a random experiment that is conducted 20 m ahead of crossroad. Due to these aspects, the transition state diagram has to adapted accordingly. The modified state transition diagram is depicted in Figure 3. It incorporates two states where random experiments are conducted for deciding upon user's future movements. In the initial state, it is determined whether the user continues moving without changing its direction or whether the user makes a turn at the next crossroad. If the user is said to turn, another random experiment is performed at the crossroad for deciding whether to turn left or right. Both random experiments have two possible outcomes with equal probability. The respective locations where these random experiments are conducted are shown in Figure 4. For example,

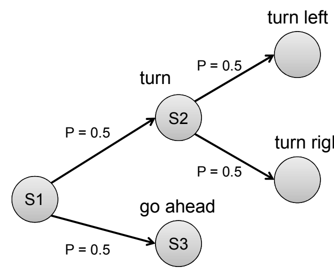

Fig. 3. Modified state transition diagram

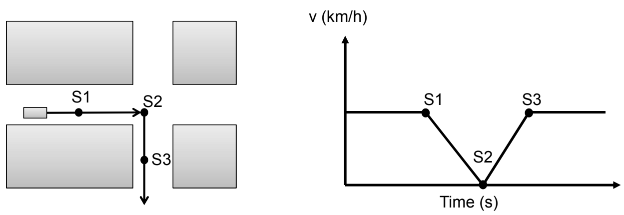

Fig. 4. Important locations and corresponding changes in user velocity

at position S1 the user decides to turn. Consequently, the user linearly decreases its velocity close to zero until the crossroad is reached. At position S2, the decision for a right turn is taken. After having made a turn, the user's velocity is linearly increased to its original velocity as shown in Figure 4. In case movement direction is not altered, the users keep on moving at its original velocity (S3). Further, it should be noted that the deceleration of one user on a specific lane also affects following vehicles, which slow down as well in order to maintain a certain distance to the vehicle ahead.

Moreover due to the nature of urban environments, cellular users moving in these environments may face severe and abrupt changes in receive signal levels, which in the worst case result in connection drops. In order to pro-actively prevent these situations, where e.g. link rate decreases, handover execution is triggered too late, or even the connection dropped, a context-enhanced user movement prediction scheme is developed. Therefore, several types of context information are used. Besides samples of user location information, velocity information, or more precisely, changes in user velocities are exploited. User location and velocity information is sampled at least once at a distance more than 20 m as well as within a distance of 20 m ahead of a crossroad. User location information may be acquired using network centric positioning technologies, such as Uplink Time Difference of Arrival (UTDOA) measurements, or provided by the terminal, e.g. Assisted GPS (A-GPS). Velocity can be inferred from Doppler shifts of uplink signaling or by increasing location information sampling rate.

The exploitation of location and velocity information allows for predicting whether users continue moving straight ahead or whether they will make a turn. However, the turn direction cannot be predicted without further information. Here, the predictor can only make a guess.

IV. Performance Evaluation

In the following, changes in user location and velocity are exploited for predicting future user movements. Further, achievable performance gains with respect to mobility-related KPIs, such as HO failures and connection drops, and system throughput are evaluated.

First, the accuracy of the the applied prediction scheme is analyzed, where different user velocities (25, 50, 75 km/h) and prediction horizons (2.5, 5, 7, 10 s) are considered. Performance results are obtained by Monte Carlo simulations consisting of 200 vehicular users that move through the considered street layout for a time period of 300 s. Figure 5 illustrates the CDF of observed deviations of predicted locations from actual user locations for different user velocities and prediction horizons. In case of user velocities of 25 km/h and a prediction horizon of 2.5 s, the prediction error is less than one meter in 80% of the cases. In contrast, prediction error for a user speeds of 75 km/h is 14 m or less in 80% of the results for the same prediction horizon. In essence, prediction inaccuracy increases with increasing velocity and prediction horizon. In the following, the prediction scheme and different prediction horizons, depicted in Figure 5, are applied for pro-actively triggering HO processes. Figure 6 shows the overall throughput against simulation for the considered prediction settings, where infinite user traffic demands are assumed. As expected, user velocity and the prediction accuracy have a huge influence on the resulting overall throughput. Best performance results can be achieved for a user speed of 25 km/h and a prediction horizon of 5 s, where throughout is increased by 39%. For 50 and 75 km/h, maximum achievable gains are 31% and 19%, respectively. It should be noted that there are cases where throughput performance using movement prediction is worse than without prediction. For example, at a user speed of 75 km/h and using a prediction horizons of 7 or 10 s, incorporating movement prediction results yields only marginal or no improvements at all. In summary, reasonable choices of prediction horizons depend on observed user velocities. An interesting finding is that a prediction horizon of 5 s yields higher throughput values for users moving at 25 or 50 km/h than a horizon of 2.5 s. In contrast, in case of users moving at 75 km/h, only a short prediction horizon of 2.5 s results in improved overall throughput.

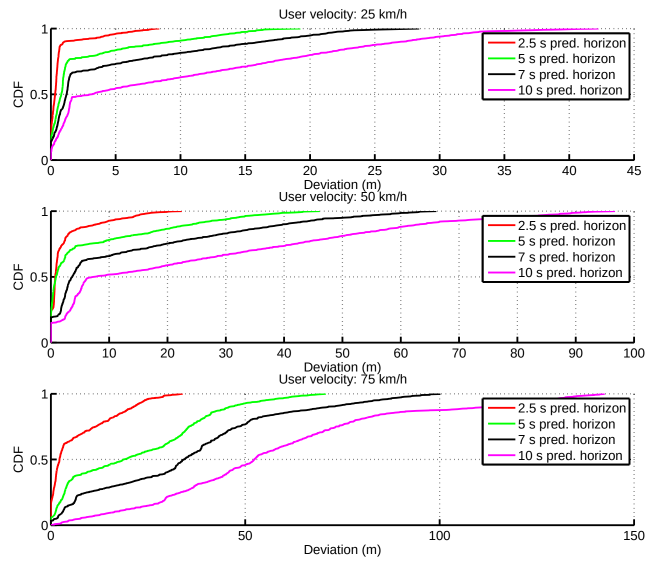

Fig. 5. Deviation of predicted locations from actual user locations

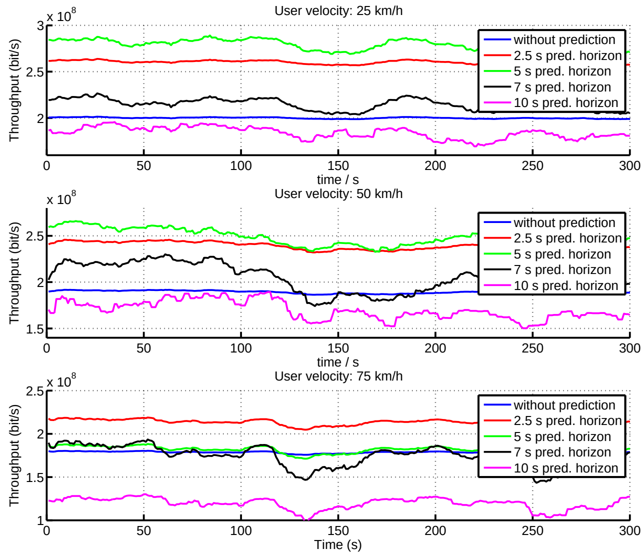

Fig. 6. Overall throughput for different prediction horizons

In order to model real-world deployment and user mobility aspects, system modeling and performance evaluation is closely aligned to the envisioned model for a *dense urban information society* as proposed by the METIS 5G project [9] as illustrated in Figure 1. Important simulation parameters used in the following are summarized in Table I. The specific user

TABLE I. SIMULATION PARAMETERS

Parameters	Value
Simulation time	180 s
User speed	50 km/h
Bandwidth per BS	10 MHz
BS transmit power	BS0: 49 dBm, BS1-12: 46 dBm
Minimum coupling loss	BS0: 70 dB , BS1-12: 53 dB
HOM, TTT, HO execution time	3 dB, 0.36 s, 0.1 s
Link-to-system mapping (SISO) [16]	$C = \eta_{eff}\ B_u\ \log_2(1+SINR_{eff})$

transmission bandwidth B_u is determined based on service requirements and stated in multiples of Physical Resource Blocks (PRBs), where each PRB has a bandwidth of 180 kHz. The overall system efficiency factor η_{eff} is set to 0.57 (cf. [16]). Radio propagation models follow those stated in [9] taking urban macro and micro cell outdoor-to-outdoor propagation characteristics into account. For example, in case of signals propagating across building edges, a specific 3D path loss model (cf. [9]) is used that accounts for refraction and diffraction effects. Further, 200 vehicular users are randomly dropped onto the street layout, where they move at predefined velocity. If they approach crossroads, they follow the behavior shown in Figure 3 and Figure 4. In order to determine to what extent context information can help to improve system performance, it is assumed that current user positions and their movement traces are exactly known, e.g. based on aggregated database knowledge. Figure 7 illustrates achievable performance gains with respect to mobility-related event counters, such as connection drops or HO failures, if user movements are perfectly estimated. Regarding HO failures, the exploitation of user movement estimates results in significantly reduced number of HO failures. Here, a reduction of 46% is achieved, however at the cost of an increase in overall

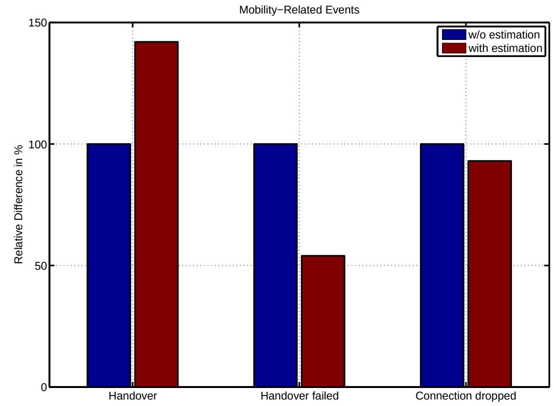

Fig. 7. Achievable gains with respect to mobility-related event counters

number of HOs by more than 40%. Hence, more HOs are anticipated and triggered before connections are dropped. In terms of connection drops, system performance is enhanced by approximately 10%. For benchmarking system performance with respect to BS load and throughput, the following schemes are considered:

- *Reference*: No movement information is available.
- *Alternative BS*: User movements and corresponding receive signal levels are predicted 10 s ahead. If receive signal level is predicted to fall below target threshold within prediction horizon, an alternative BS is identified and handover is performed.
- *Predictive RRM*: In addition to movement and signal level prediction, the best time slot with respect to SINR is predicted for scheduling user transmissions.

Further, system performance is evaluated with respect to two different service types: Constant Bit Rate (CBR) and best-effort. For CBR service, a constant bit rate of 600 kbps is required. Figure 8 depicts sum throughput and load, respectively. Table II lists sum throughput and load values as well as

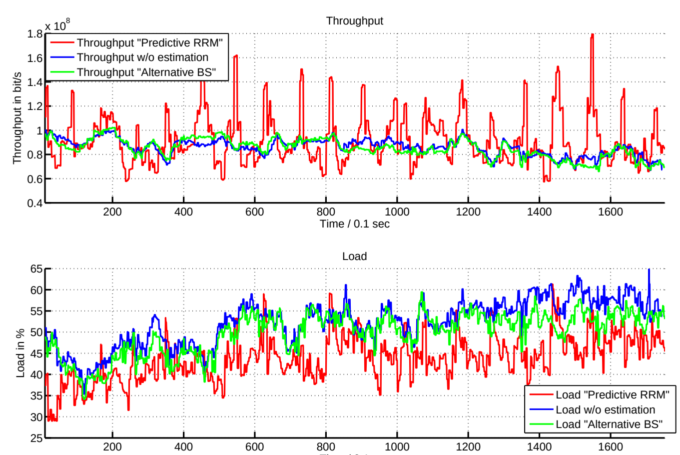

Fig. 8. CBR service performance benchmark with respect to sum throughput and load

obtained gains. Given the strict bit rate requirement, gains with respect to throughput are rather marginal. However in terms of overall load, moderate improvements are obtained in case of *Predictive RRM*.

TABLE II. PERFORMANCE RESULTS FOR CBR SERVICE

Parameter	Scheme	Value	Gain
Throughput	Reference	85.1 Mbps	-
	Alternative BS	86.4 Mbps	1.5%
	Predictive RRM	92.2 Mbps	6.2%
Load	Reference	52.5%	-
	Alternative BS	50.1%	4.7%
	Predictive RRM	44.0%	19.1%

For the best-effort service, the so-called full buffer model [10] is used for modeling situation of infinite traffic demands. Further, different scheduling strategies are considered for the *Alternative BS* and *Predictive RRM* scheme, respectively. In case of *Alternative BS* scheme, resources are distributed equally among connected UEs in a fair manner. However, *Predictive RRM* scheme only schedules the UE that is experiencing best receive conditions (maximum carrier-to-interference (C/I) ratio) among all connected UEs in each time slot. Figure 9 illustrates system performance with respect to sum throughput. Table III summarizes sum throughput

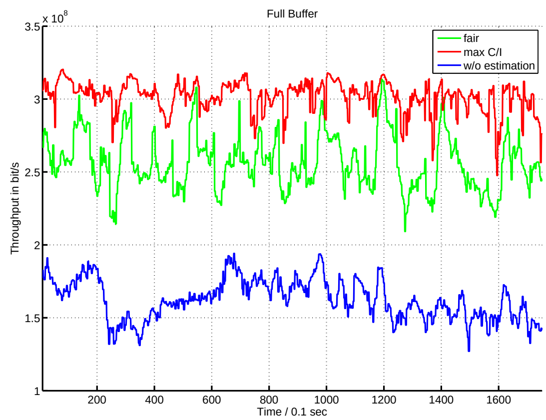

Fig. 9. Best-effort service performance benchmark with respect to sum throughput and load

performance and achieved gains. Regarding overall throughput,

TABLE III. PERFORMANCE RESULTS FOR BEST-EFFORT SERVICE

Parameter	Scheme	Value	Gain
Throughput	Reference	162.7 Mbps	-
	Alternative BS	258.1 Mbps	58.6%
	Predictive RRM	322.6 Mbps	98.2%

significant performance improvements of approximately 100% are obtained in case of $\max C/I$ scheduling and assuming permanently full BS buffers. Even if no predictive scheduling is performed and users are assigned resources in a fair manner, throughput can still be enhanced by approximately 60%. In this specific scenario, these performance figures can be considered as an upper bound for the exploitation of context information, such as user movement estimates. Moreover, if information, e.g. environment-specific radio maps, can be used for predictive user scheduling, system performance can be boosted even further.

V. CONCLUSION

The objectives of this paper have been twofold. First, accuracy and applicability of a prediction scheme that assumes realistic user mobility modeling was investigated. Then, achievable performance gains using context estimation, e.g. movement and SINR, are evaluated on system level considering realistic 3D deployment, mobility, and propagation models. It has been shown that overall throughout can be enhanced up 39%, 31%, and 19% for user velocities ranging from 25, 50, 75 km/h, if prediction horizons are set accordingly. Here, larger improvements may be feasible, if scheduling decisions account for prediction results. Further, limits of context prediction exploitation have been explored. Here, gains of 50% or up to 100% were achieved by applying user movement estimation and joint movement and SINR estimation, respectively.

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