

A Model for Throughput Prediction for Mobile Users

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Abstract—In this paper we propose a stochastic model to predict user throughput in mobile networks. In particular, the model accounts for uncertainty such as random phenomena (e.g., fast fading) or inexact information (e.g., user location) to derive the statistical distribution of the user throughput. Such a model is highly useful for aiding scheduling and resource allocation decisions. In addition, we provide a taxonomy of prediction techniques to investigate error sources and the main characteristics of prediction accuracy. Finally, we show the versatility of the model by analyzing LTE user throughput for the case where knowledge of either the user’s actual position or the congestion level in the cell is inexact.

I. INTRODUCTION

The rapid growth of mobile traffic volume [1] is taxing the capacity of current mobile networks and poses a significant problem for mobile operators. Augmenting the network capacity to cope with this traffic or offloading the traffic to other wireless technologies such as WLAN may not always be the best solution since the former is very costly and the latter may not work in all cases [2], [3]. As a consequence, it is highly important to try to reduce traffic volume and increase network efficiency (while at the same time rolling out faster mobile networks). In this context, it is beneficial to leverage forecasted user throughput to improve the resource allocation and to reduce cell congestion.

For instance, the Piecewise Constant Threshold (PCT) algorithm [4] sends more data when the signal quality (i.e., the Signal to Interference and Noise Ratio – SINR) is high, while primarily relying on buffered data while it is low. Similarly, [5] adopts an anticipatory scheduling algorithm to forecast and overcome channel outages and [6], [7] optimize resource utilization in vehicular environments. All of these solutions aim at scheduling traffic when capacity is abundant, so that congestion is reduced and, consequently, fewer resources are needed to serve the overall traffic volume.

The above works depend on the capability of predicting the future resource availability and many of them in fact analyze their algorithm’s performance under the assumption of perfect knowledge. Network predictability is thoroughly studied, for example, in [8]. This work also affirms that cellular network data shows a high level of self-similarity and user “mobility directly impacts resource usage.” Thus, being able to model [9] and forecast [10] human mobility patterns aids predicting network resource availability for mobile users.

The main contribution of this paper is a novel synthetic model representing the impact of estimation and prediction errors on the bandwidth availability statistics to be able to

study network resource optimization problems under forecasting uncertainties. In order for the model to account for the many different error sources, we analyze state of the art prediction models for both network resources as well as user mobility, which we subsequently organize in a taxonomy based on the time-scale and granularity of the prediction.

The rest of the paper is structured as follows. Section II provides an overview and taxonomy of predictors upon which our model is based. In Section III, we discuss in detail the model for network resource availability under estimation and prediction errors. The model is applied to LTE cellular systems in Section IV. Finally, Section V concludes the paper.

II. TAXONOMY OF PREDICTORS

In this section, we analyze predictors for both user mobility (II-A) and network resource availability (II-B) in order to understand the forecasting capability for mobile systems and the accuracy of the available solutions. The considered works cover a wide range of time scales, location granularities and levels of accuracy. To provide a comprehensive model, we classify them in three categories according to their time and space granularity.

The first group [11]–[14], (1)-*net*, is the most coarse: network performance is modeled by analyzing the whole network at once, with a time scale on the order of minutes to hours; users are statistically mapped to base station cell ID or geographic location, i.e., predictions obtained by these models concern average throughput achievable in the location a given user is most likely to be found.

Algorithms in the second group [15]–[18], (2)-*cell*, combine user mobility information and network location specific information to refine prediction granularity. Predictors belonging to this group aim at predicting the next cell a user is likely to visit, the congestion level in that cell and the time of the visit. Its timescale is between tens of seconds and a few minutes.

The third group [19]–[22], (3)-*user*, comprises the predictors with highest time granularity: in fact, most of the solutions in this group leverage filtering techniques and historical data. The aim, here, is to model the fast bandwidth variations experienced by the users on a timescale of tens of milliseconds up to a few seconds.

Table I groups the papers into the three categories and also provides a high level description of the papers. The “Cat.” column specifies the name of the category, while the “Accuracy” column provides an evaluation of the effectiveness of the techniques. Here, we use the ratio between the mean square error of the prediction and the standard deviation of the original

TABLE I. PREDICTION TAXONOMY

| Ref. | Cat. | Accuracy | Notes |
|------|----------|------------------------------|-----------------------------------------------------------------------------------------|
| [11] | (1)-net | $c_r \sim 0.8$ | Provides a model for the number of user in a cell. |
| [12] | | $\varepsilon \sim 0.15$ | ARIMA models and wavelet MRA. |
| [13] | | $\varepsilon > 0.01$ | GARCH-ARIMA accurately models static high-speed network traffic. |
| [14] | | $\varepsilon \in [0.01 - 1]$ | Evaluates multi scale and s -sample prediction. |
| [15] | (2)-cell | $c_r \in [0.5 - 0.72]$ | Compares Markovian (better) and Lempel-Ziv models. |
| [16] | | $\varepsilon_l \sim 2$ m | User trajectory prediction. |
| [17] | | $c_r \in [0.2 - 0.7]$ | Route prediction on GPS data. |
| [18] | | $c_r > 0.8$ | Using pre-filtered data and Markov models. Prediction possible in the 98% of the cases. |
| [19] | (3)-user | $\varepsilon \in [0.05 - 2]$ | Empirical study on user traces using wavelet approximations and filtering. |
| [20] | | $\varepsilon \sim 1$ | First attempt at mobile system bandwidth prediction. |
| [21] | | n/a | Complete solution for mobile bandwidth forecast. |
| [22] | | $\varepsilon \sim 0.01$ | Spatial and temporal dynamics characterization of mobile Internet traffic. |

time series (e.g.: the user throughput, the bandwidth availability, etc.) $\varepsilon = \text{MSE}(\hat{x})/\sigma_x^2 = \sum_i (x_i - \hat{x}_i)^2 / \sum_i (x_i - \mu_x)^2$, where x_i and \hat{x}_i are the i -th samples of the original time series and their predictions, respectively, and σ_x and μ_x are the standard deviation and the average of the original time series, respectively; c_r is the correct prediction rate defined as the ratio between the number of times the predicted location of a user is correct and the number of attempts; and ε_l represents the distance between the predicted and the correct user position.

A. Mobility Predictors

The most common methods to locate a mobile terminal are, in order of decreasing accuracy, the Global Positioning System (GPS), WiFi, and cellular network positioning. These solutions can identify a terminal's position with an average error on the order of 10, 100 and 500 meters, respectively [23].

Theoretical works, such as [9] and [10] studied characteristics of human behavior and found that an appreciable level of self-similarity exists among behavioral patterns and that, within due limits, forecasting is possible. Among the many studied properties, we highlight the one asserting that the probability of a user to be found in a given location is approximately inversely proportional to the location rank.

Some predictors aim at estimating the next user position on a grid representing network cells: [15]₍₂₎ compares Markovian and Lempel-Ziv models trained with the sequences of locations a user visited in the past, while [11]₍₁₎ studies the accuracy of mobility modeling. Notably, the first paper comes to the conclusion that second order Markov models provide a good trade off between complexity and accuracy achieving a correct prediction rate $c_r \in [0.5 - 0.72]$ on mobility traces collected from more than 6000 users of Dartmouth College's wireless network. The second paper provides an effective way to estimate the number of users in a cell and, consequently, the congestion level.

Other predictors deal with routes and trajectories. [16]₍₂₎ uses 1-sample predictions of user position to improve the performance of a routing protocol. (An s -sample prediction computes the first s unknown samples of a given time series.) The location prediction accuracy is claimed to be on the order of a few meters, with a position error $\varepsilon_l \sim 2$ m. The work in [17]₍₂₎ focuses on predicting complete routes from historical GPS data and obtains a $c_r \in [0.2 - 0.7]$. Here, the best results are obtained when excluding single trips from the dataset.

Finally, [18]₍₂₎ uses second and third order Markov models trained on a pre-filtered leap graph to model and predict cellular user mobility. The solution is able to achieve a $c_r \geq 0.8$ in 98% of the cases. Finally, recent works, such as [7] and [21]₍₃₎, directly exploit position information obtained from navigation systems to map bandwidth availability to locations. While these solutions provide a prediction that is based on the actual intended destination of the user, the accuracy of the prediction is still limited by the accuracy of the positioning system and the possibility of user detours. To the best of our knowledge, a detailed study linking location prediction accuracy to bandwidth/throughput prediction accuracy does not exist.

B. Bandwidth Predictors

One of the most relevant studies on traffic dynamics for cellular networks is [8], which conducted the first detailed wide scale analysis of network usage and subscriber behavior. The paper characterizes mobility and temporal activity patterns and identifies their relation to traffic volume. Traffic has been analyzed from the base station point of view, identifying its variations over space and time.

Earlier works such as [12]₍₁₎, [19]₍₃₎ and [13]₍₁₎ studied different filtering techniques, namely MEAN, LAST, BM, MA, AR, ARMA, ARIMA, and FARIMA, all of which are different combinations of moving average and autoregressive filtering. We refer the interested reader to the source papers for the details.

Although different papers use slightly different metrics, the following conclusions can be drawn: low order filtering techniques coupled with smoothing solutions (e.g., wavelet MultiResolution Analysis (MRA) or wavelet approximation) are able to provide 1-sample static network traffic predictions with an error as low as $\varepsilon = 0.05$ and almost always lower than the variance of the original signal, $\varepsilon = 1$. (In the latter case, the predicted sample error would be as large as those that would have been obtained by generating random samples from a distribution with the same variation as the original signal). The error decreases with larger timescale and smoother approximation of the signal.

Subsequent work in [14]₍₁₎ compares FARIMA and GARCH filtering techniques in terms of both time scale and the number of predicted samples s . Results obtained from Internet traffic traces show that GARCH outperforms FARIMA, achieving an error that is four time smaller. The

authors confirm that the error decreases with increased signal timescales and increases with the number of predicted samples s . In particular, the error becomes as high as the variance of the original signal for $s = 10$ and $s = 100$ samples for FARIMA and GARCH, respectively. Also, GARCH errors are slightly smaller than half the variance for $s = 10$ samples and beyond.

[20]₍₃₎ and [22]₍₃₎ study resource availability in mobile systems. The former observes no significant correlation within a single trip, but throughput traces show a higher degree of self-similarity during repeated trips. The latter paper, instead, classifies traffic according to spatial features and proposes a multi-class model to predict traffic, achieving promising results ($\varepsilon \sim 0.01$). Finally, although standard filtering techniques for static environments are less effective when applied to throughput of mobile nodes, they provide better accuracy when location is used as a context.

III. BANDWIDTH AVAILABILITY MODEL

Based on the previous taxonomy, this section determines the main error sources and their impact on the statistical distribution of the predicted throughput. Fig. 1 shows examples of effects of errors on throughput prediction: the x -axis represents how far into the future the prediction is made, while the y -axis represents the predicted throughput and the corresponding estimation error. Note that purpose of the figure is to graphically exemplify the predictor categories; it is primarily intended to provide an intuition.

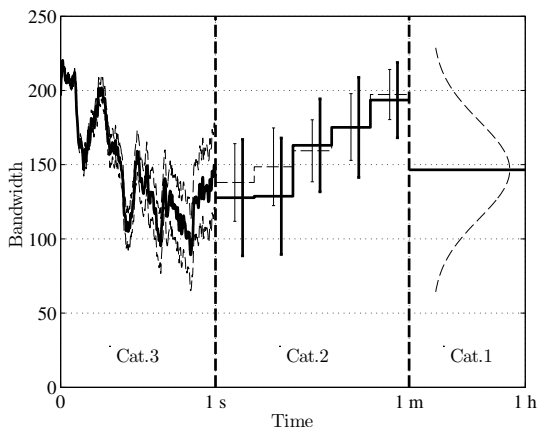


Fig. 1. Bandwidth forecasting examples: category 3, 2 and 1 predictor outputs are shown on the left hand side, in the center and on the right hand side, respectively.

The figure examines the three categories of the taxonomy starting from (3)-*user* category on the left hand side. Here, the solid line represents the prediction itself, while the two dashed lines represent the confidence range of the prediction. Although the accuracy degrades with time, predictors belonging to this category are able to closely follow the throughput variations. As soon as the confidence range becomes as large as the signal's standard deviation, category (2)-*cell* predictors becomes as effective as category (3)-*user* predictors.

In the center, predictions obtained from the category (2)-*cell* are shown. Here, the predictions are averaged over longer

time periods and their variability is represented by error bars. The solid line represents the actual prediction average along with its standard deviation, while the dashed line represents the same for the original signal. Predictors in this category infer user throughput from their position and statistics of the corresponding network cell.

Whenever it is not possible to predict the next user location, only predictors in category (1)-*net* can be used (right hand side of Fig. 1). They derive an estimate of user throughput from general network information using, for example, the generic distribution of user throughput in the overall network (shown in the figure as a dashed line).

To model the impact of errors on the predictors, we start from a simple formulation of the phenomenon itself. A very popular user throughput model can be found, for instance, in [24]. Here, the throughput T of a user with a distance of d kilometers to the transmitter and competing with N other users uniformly distributed within the coverage area of the transmitter, is represented as a function of the Signal to Interference plus Noise Ratio (SINR) γ , and N :

$$T = g_T(\Gamma, N) = T_0 \eta / N, \quad (1)$$

where $\Gamma = 10 \log_{10} \gamma$ is the SINR in dB, T_0 is a parameter specific to the actual cellular system and $\eta = g_\eta(\Gamma)$ is the spectral efficiency for that SINR. The SINR is a function of d and the fast fading gain r :

$$\gamma = g_\gamma(d, r) = \gamma_0 r / d^\alpha, \quad (2)$$

where γ_0 is a technology specific parameter and α is the pathloss exponent.

For what concerns errors themselves, different predictors are impacted by different error sources: for instance, those belonging to the third category try to model the short term behavior of the achievable throughput starting from past information. Thus, predicted throughput $\tilde{T} = T + e_T$, is the sum of the actual throughput and the prediction error. Given that the error e_T has a probability density function (pdf) $f_{e_T}(e)$, the predicted throughput will have a pdf $f_{\tilde{T}} = f_{e_T}(e - T)$. Also, in the worst case the s -sample prediction can be modeled as the sum of s i.i.d random variables with distribution $f_{e_T}(e)$. Thus the s -sample predicted throughput distribution can be obtained as $f_{\tilde{T}(s)} = f_{e_T}((e - T)/s)/s$, which will have an expected value $\mu_{\tilde{T}(s)} = T(s) + s\mu_{e_T}$ and standard deviation $\sigma_{\tilde{T}(s)} = s\sigma_{e_T}$. Note that increasing s makes the prediction less and less accurate up to a point where the standard deviation of the prediction becomes comparable to the variability of the throughput σ_T .

Beyond this point using this type of predictors is useless and category 2 and category 1 predictors should be used. In this case, most of the predictors try to first estimate system parameters, such as the distance d and the number N of users and, from those, estimate the throughput distribution. Thus, in order to model the latter from the distributions of d and N , we will proceed as follows. First we analyze the distribution of the SINR given that N user are competing for the channel. It depends on the joint distribution $f_{r,d}(r, d|N)$, of the fading

TABLE II. MCS COEFFICIENTS

| Modulation CQI | N/A | QPSK | | | | | | 16QAM | | | 64QAM | | | | | |
|-------------------|-----------|-------|-------|-------|-------|------|------|-------|------|------|-------|-------|-------|-------|-------|-------|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| G_i | $-\infty$ | -6.00 | -4.14 | -2.29 | -0.43 | 1.43 | 3.29 | 5.14 | 7.00 | 8.86 | 10.71 | 12.57 | 14.43 | 16.29 | 18.14 | 20.00 |
| c_i | 0 | 0.15 | 0.23 | 0.38 | 0.60 | 0.88 | 1.18 | 1.48 | 1.91 | 2.41 | 2.73 | 3.32 | 3.90 | 4.52 | 5.12 | 5.55 |

gain r and the distance d according to (2):

$$f_\gamma(\gamma|N) = \int_0^\infty f_{r,d}(g_\gamma^{-1}(\gamma, d), d|N) \left| \frac{\partial g_\gamma^{-1}(\gamma, d)}{\partial \gamma} \right| dd, \quad (3)$$

where $g_\gamma^{-1}(\gamma, d)$ is the inverse function of (2) and we remove the variable d from the joint distribution $f_{\gamma,d}(\gamma, d|N)$ by integrating it on its whole support. Note that it is important to condition on N in order to account for opportunistic gain effects.

The last step requires to compute the throughput from the SINR using $g_\eta(\Gamma)$, which can be a piece-wise constant or other non-differentiable functions. In this case it is easier to use the cumulative distribution functions (CDF), since we can avoid to use the derivative. In fact, the throughput CDF $F_T(x|N) = P(T \leq x) = P(g_T(\gamma) \leq x) = P(\gamma \leq g_T^{-1}(x)) = F_\gamma(\gamma^*|N)$, where $\gamma^* = g_T^{-1}(x)$. Thus,

$$F_T(x|N) = \int_0^{\gamma^*} f_\gamma(\gamma|N) d\gamma. \quad (4)$$

The SINR and the throughput distributions can be obtained removing the dependency on N by multiplying by the probability mass function (pmf) of the number of user p_N , and summing over N . Thus,

$$F_\gamma(\gamma) = \sum_{i=1}^{M_N} p_i \int_0^\gamma f_\gamma(\gamma|i), \quad (5)$$

$$F_T(x) = \sum_{i=1}^{M_N} p_i F_T(x|i), \quad (6)$$

where M_N is chosen so that $p_{M_N} > 0$ and $p_{M_N+i} = 0, \forall i > 0$.

Note that, thanks to the independence of the fading and the distance distributions, their joint distribution can be written as the product of the two distributions:

$$f_{r,d}(r, d|N) = f_r(r|N) f_d(d). \quad (7)$$

It is easy to customize the model by modifying the distributions of three basic random variables, namely p_N , $f_d(d)$, $f_r(r|N)$. In particular, it is possible to include temporal and/or spatial dependencies by letting the distributions vary according to the location and the time.

IV. RESULTS

In this section we apply the model to the case of an LTE cellular system as defined in [25] adopting a Proportional Fair (PF) scheduler modeled according to the results in Section II.D and III.B in [24].

In particular, we provide more specific definitions for some of the previous parameters: $T_0 = N_R B_R$, where N_R is the number of resource blocks and B_R is channel bandwidth;

$\gamma_0 = 10^{(P_T - N_f + C)/10}$, where P_T is the eNodeB transmission power in dB N_f is the noise plus interference power in dB and $C = 128.1$ dB is a constant modeling other effects (such as antenna gains, frequency dependency, etc.); $g_\eta(\Gamma) = c_i$ if $G_i < \Gamma \leq G_{i+1}$ with $i \in \{0, \dots, 15\}$ and $G_{16} = \infty$. c_i is the bit efficiency of the modulation of the i -th Modulation and Coding Scheme (MCS). The values for c_i and G_i used in the paper are derived from [25] and are given in Table II.

In order to derive the exact expression for the SINR and the throughput distributions, we need to specify the distributions for the fading gain r , the distance d , between the user equipment and the eNodeB, and the number N , of user in the cell.

For what concerns the fading gain, in this paper we follow the results of [24], which models the opportunistic gain obtainable by the PF scheduler as follows:

$$f_r(r|N) = N(1 - e^{-r})^{N-1} e^{-r}. \quad (8)$$

This gain is associated to the higher probability for a user to be scheduled having a high SINR, when more users are competing for the channel.

The distance distribution $f_d(d)$, is obtained as the sum of two components: the actual distance distribution and the error committed in evaluating and/or predicting it. In the following, we analyze the case of a static user, whose distance is obtained with the three most common methods: GPS, WiFi and cell signal strength. In all the three cases we model the distance with a Gaussian distribution with an average $\mu_d = d^*$, equal to the correct user position d^* , and a standard deviation $\sigma_d = \{10, 100, 500\}$ meters, for GPS, WiFi and cell localization [23], respectively. Since the Gaussian distribution can lead to positive probability for negative values, we will normalize by $1 - \Phi(-\mu_d/\sigma_d)$, where $\Phi(x)$ is the CDF of a Gaussian distribution computed in x .

Similarly, the distribution of the number of users N , depends both on the actual value N^* , and the estimation error. As above, we take the Gaussian distribution as a reference:

$$p_i = \Phi((i - \mu_N)/\sigma_N) / (\sigma_N \sum_j p_j) \quad (9)$$

with $i \in \{1, \dots, M_N\}$, where $\mu_N = N^*$ is the average value of the distribution and $\sigma_N \in \{0, 1, 3, 10\}$ are the standard deviation values we studied in the following examples of Fig. 2 and Fig. 3.

In these two examples, we focused on a single error at a time so as to separate the effects of an erroneous knowledge of N and d . The plot presents results for which we applied the aforementioned distributions to (3), obtaining:

$$f_\gamma(\gamma|N) = \int_0^\infty \frac{N d^\alpha}{\gamma_0 \sigma_d} \left(1 - e^{-\frac{\gamma d^\alpha}{\gamma_0}}\right)^{N-1} e^{-\frac{\gamma d^\alpha}{\gamma_0}} \phi\left(\frac{d - \mu_d}{\sigma_d}\right) dd. \quad (10)$$

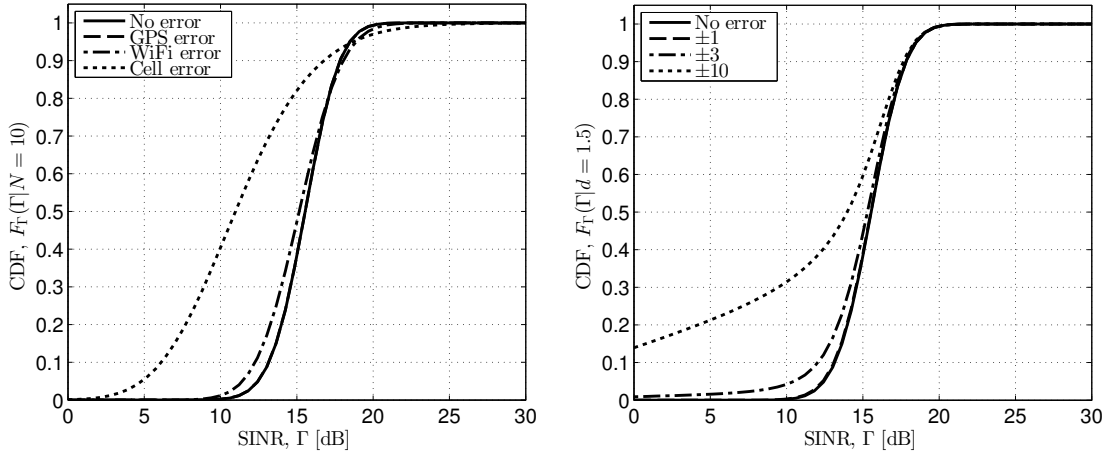


Fig. 2. Plots of the SINR CDF F_Γ , given a perfect knowledge of $N = 10$ (left) or a perfect knowledge of $d = 1.5$ Km (right). In the former case the standard deviation σ_d , of the distance is set as that of the most common localization systems, while in the latter $\sigma_N \in \{0, 1, 3, 10\}$.

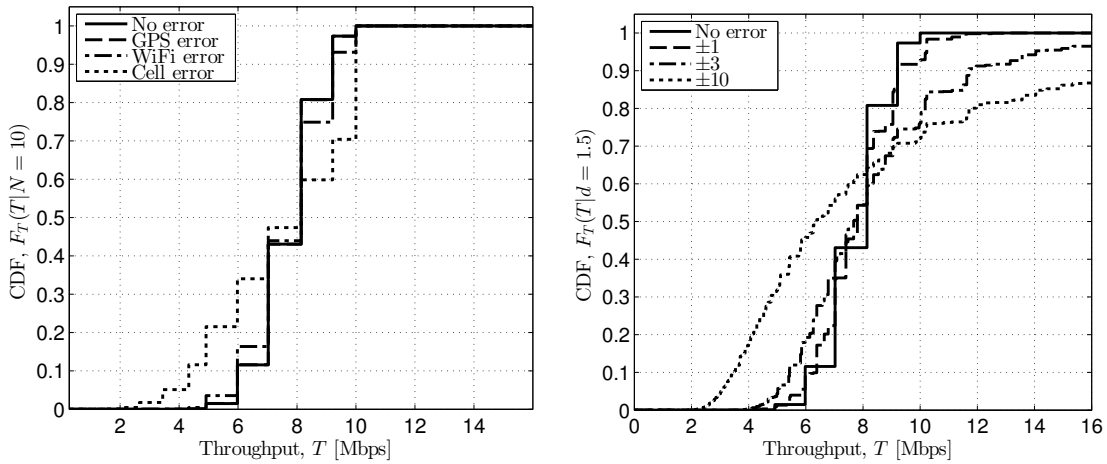


Fig. 3. Plots of the throughput CDF F_T , given a perfect knowledge of $N = 10$ (right left side) or a perfect knowledge of $d = 1.5$ Km (right hand side). In former case the standard deviation σ_d , of the distance is set as that of the most common localization systems, while in the latter, $\sigma_N \in \{0, 1, 3, 10\}$.

Now it is possible to compute γ^* as

$$\begin{aligned} \gamma^* &= 10^{g_\eta^{-1}(\frac{TN}{N_R B_R})/10} \\ \gamma_{i,N} &= 10^{G_{i+1}/10} \text{ with } \frac{c_i T_0}{N} \leq T < \frac{c_{i+1} T_0}{N}, \end{aligned} \quad (11)$$

which depends on both the bandwidth and the number of users. Now it is possible to compute (5) and (6), by using (10), (11) and (9).

In particular, Fig. 2 (left) shows $F_\Gamma(\Gamma|N = 10)$, using $f_d(d) = \mathcal{N}(\mu_d = d^* = 1.5, \sigma_d)$, and $\sigma_d \in \{0, 0.01, 0.1, 0.5\}$ to represent a static user, whose position is obtained with a localization error ranging from perfect knowledge to the worst approximation of a cell system localization. The figure shows that only with the precision of GPS is it possible to accurately estimate the statistical distribution of the SINR and that, if GPS information is lacking, the SINR prediction distribution becomes very wide even for static users.

Similarly, Fig. 2 (right) shows $F_\Gamma(\Gamma|d = 1.5)$ and the number of users distributed according to (9) using $\mu_N = 10$, $\sigma_N \in \{0, 1, 3, 10\}$ and $M_N = \mu_N + 5\sigma_N$. Again, for low σ_N , the distribution maintains the original shape, but as soon as $\sigma_N > 1$ the SINR distribution starts to get wider and is shifted towards the left. Note that, an error on N implies that $P(\tilde{\gamma} > \gamma) = 0 \forall \gamma$, which is a direct consequence of the modeling of the opportunistic gain of the PF scheduler.

The last two figures, Fig. 3 (left) and Fig. 3 (right), study F_T with errors on d and N , respectively. The error distributions are shaped as above, but this time the discontinuities of $g_\eta(\gamma)$ are evident. In particular, for a wider SINR distribution a larger number of MCS get positive probability of being used. Also, on the right hand side figure, the throughput CDF becomes smoother and smoother for increasing σ_N . This is due to the wider range of $\gamma_{i,N}$ introduced by (11).

Besides the trivial conclusion that the throughput distribu-

tion widens as the uncertainties grow, our model allows to compute where the correct value of the throughput is more likely to be found when a given prediction is computed. Also, the model allows to estimate the likelihood of the throughput to fall below a given threshold, thus enabling the study of resource allocation techniques when future information has limited reliability.

V. CONCLUSION

In this paper we proposed a novel stochastic model for the user throughput prediction in mobile networks. The model takes into consideration the most relevant sources of prediction inexactness, such as random phenomena (e.g., fast fading) or imprecise information (e.g., user location). In fact the model derives the statistical distribution of the user throughput starting from those of the error sources. Also, the model allows for a closed form analysis of throughput prediction, which, in turn, enables to study the likelihood of forecasting-based optimization techniques to achieve their objective.

We built our model based on a study of throughput prediction for mobile networks mechanisms: we provided a taxonomy of the existing solutions by grouping them in three categories characterized by time scale and granularity of the prediction. In particular, we found that there exist very fine grained predictors capable of capturing the fast variations of the throughput, predictors that are able to forecast the next user position in a medium time scale and, from that, estimate the throughput statistics and, finally, very general solutions that provide the overall statistic of a user, when it is not possible to associate it to a given location.

From our analysis it emerges that there is no single predictor performing well in all the three categories. In addition, most of the solutions do not provide the confidence interval of their predictions. Thus, we plan to continue the research on this subject by developing a general prediction system combining the best solutions of the three categories and providing both a throughput prediction and its statistical distribution to understand the reliability boundary. Finally, the general predictor will be further applied to the study of network resource allocation optimization under forecasting uncertainties.

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