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Outage Prediction for URLLC in Rayleigh Fading

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***Abstract*—A major challenge for the realization of ultra reliable low latency communications (URLLC) systems is the fast fading of wireless channels and the therewith associated outages. To overcome the fading, diversity concepts, as well as transmissions with low modulation order and low code rate are widely considered. However, these methods have an undeniably high resource consumption. In order to reduce it, fading prediction methods can be utilized as part of the scheduling strategy. We propose a novel outage prediction approach based on a Wiener filter that significantly helps to increase URLLC system monitoring and radio resource scheduling. In this paper we focus on Rayleigh fading channels and classical Doppler spectra. The proposed outage predictor is found to work on a wide range of sampling times and also with only a few observed fading samples available. During operation, future outage probabilities can be calculated beforehand and reliability guarantees can be made. Utilizing the proposed outage prediction method increases the achievable reliability of a link by several orders of magnitude compared to best effort transmissions on a single link. Links that are operable are well identified when little movement is present and prediction of several milliseconds is sufficient.**

***Index Terms*—channel prediction, URLLC, radio resource scheduling, CQI aging**

I. Introduction

Development efforts towards Ultra Reliable Low Latency Communications (URLLC) have multiplied in recent years, due to the prospect of a whole range of new applications. These applications are, e.g., in the field of industrial production, where shorter product cycles, higher product individualization and overall increased flexibility are expected to be enabled [1]. The Tactile Internet relies on URLLC services as well and is promised to revolutionize remote interactions with the environment and even human learning [2]. Although recent studies indicate that some closed loop controlled systems as cooperative automated driving or the control of automated guided vehicle (AGV) fleets do not have as strict requirements regarding communications latency as initially assumed [3], [4], URLLC is inevitably required for control loops with higher dynamics. Round trip latency values of a few milliseconds are also important for a wide variety of applications with humans involved, e.g., teleoperating systems or virtual environments.

The ambitious Quality of Service (QoS) requirements for URLLC are highly demanding for wireless communications systems, since achieving such low latency values usually requires the communications system to be able to successfully transmit packets on the first try, implying also demands towards high communications dependability. Especially small-scale fading, which causes random fluctuations of the received power, is difficult to overcome and a major source for packet errors. Most problematic are deep fades, where the received power is low and packet errors are highly likely. Following these considerations, a two-state model for the fading can be employed, categorizing the fading in *outage* and *up* state based on a threshold value.

To be able to transmit reliably also in case of a link outage, diversity concepts can be utilized where multiple links are used for redundant data transmission in parallel. However, in order to achieve an overall outage probability of 10^{-5} at a fading margin of $F = 10\,\mathrm{dB}$, at least five selection combined, independent Rayleigh fading links are needed [5]. For lower probabilities, which are discussed for URLLC, even more parallel links are required. This results in a massive need for communications resources, raising the question of scalability when many URLLC devices need to be served. To implement resource efficient scheduling strategies we propose an outage predictor, which is able to predict future outages based on the previously observed fading. URLLC devices can then be assigned to communications resources that are predicted to be operational, reducing the resource consumption per device while simultaneously maintaining the desired QoS. Furthermore, the proposed outage predictor is capable of delivering the probability of a future outage. This probability can be used to warn upper communications layers in advance, when it is expected that not enough resources can be provided for URLLC services. Such predicted availability indications are a key enabler for ultra reliable services as discussed in [6]. Based on this information, the application is able to decide if an adaption to a worse Quality of Control (QoC) (e.g., slowing down) resulting from the reduced QoS is needed. The prediction allows the application to prepare in advance, since applying such measures usually takes some time.

Numerous small-scale fading predictors have been proposed in the literature over the last years [7], [8]. Just recently, also machine-learning-based fading prediction approaches [9], [10] were investigated. Such fading predictors have been almost exclusively analyzed in view of achievable gains in spectral efficiency (e.g., in [11]), since the metric is suited for quantifying communications resource savings. For successful URLLC system design, however, the focus shifts towards the experience of a single user, demanding for QoS-focused

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methods. Only little fading prediction research tailored to the needs of URLLC has been carried out. The authors in [12] investigated fading prediction methods for relay selection in cooperative URLLC architectures. Methods for general URLLC systems have not been presented yet.

In this work, we aim to fill this gap and extend the Wiener-filter-based fading predictor of [7] for URLLC outage prediction. Additionally to the derivation of the outage predictor, we provide an overview over the filter parameter choice for optimal prediction performance. The predictor has the potential, as shown in our simulation-based evaluations, to reduce the link outage probability significantly.

II. System Model

A simplified model for the communications system is considered to understand the fundamental performance of the outage predictor. We assume that the user equipment (UE) is connected to the base station (BS) over a single Rayleigh fading link with its complex channel coefficient $h(t)$. Furthermore, we consider additive white Gaussian noise (AWGN) $n(t)$. Hence, the transmit signal $x(t)$ and the receive signal $y(t)$ are related by

$$y(t) = x(t) \cdot h(t) + n(t) \quad . \tag{1}$$

Furthermore, we consider a constant relative movement between the UE and scatterers, resulting in a maximum Doppler shift f_m. As for this kind of investigations widely assumed in literature, we consider numerous independent multi-path components arriving at the receiver at the same time with equally distributed angle of arrivals solely in the horizontal plane. These assumptions lead to the classical Doppler spectrum with autocorrelation function

$$r_{hh}(\tau) = J_0(2\pi f_m \tau) \quad . \tag{2}$$

The UE is assumed to be simultaneously transmitting P pilot symbols for uplink channel estimation of the fading at time t, which are in the following expressed by the vector $\boldsymbol{p}$. The channel estimation is then used as input for the predictor. On the BS, a maximum likelihood (ML) estimator is considered to obtain an estimate of the complex channel coefficients

$$\hat{h}(t) = (\boldsymbol{p}^H \boldsymbol{p})^{-1} \boldsymbol{p}^H \boldsymbol{y} \quad . \tag{3}$$

This ML channel estimator is widely used in practice since it achieves the Cramér-Rao bound and is unbiased. Later on, the relationship between observation (channel estimation) and true value of the fading is of importance. Based on the ML channel estimator and the AWGN assumption we can use

$$\hat{h}(t) = h(t) + n'(t),$$
$$\mathrm{Re}\{n'(t)\}, \mathrm{Im}\{n'(t)\} \sim \mathcal{N}\big(0, \sigma_{n'}^2 = \sigma_n^2 (\boldsymbol{p}^H \boldsymbol{p})^{-1}\big) \quad . \tag{4}$$

Here, σ_n describes the variance of real and imaginary part of a single noise sample and σ_n' is the variance of white Gaussian noise overlapping the true fading value after channel estimation.

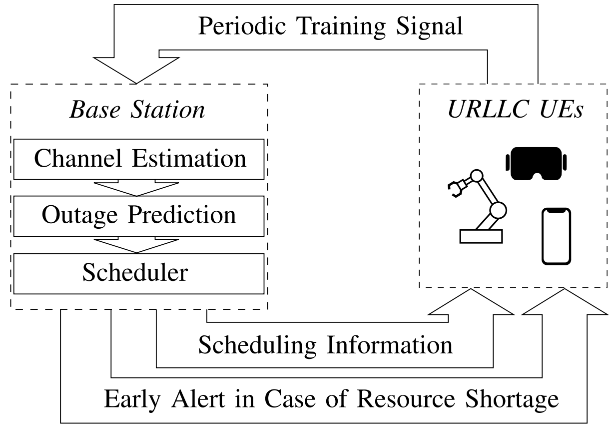

Fig. 1. Outage predictor within a base station-centered architecture.

For scheduling purposes, it is assumed that uplink channel estimations are available periodically at the BS over a large bandwidth (e.g., via sounding reference signals). Channel reciprocity is assumed such that by measuring the uplink channel, the downlink channel can also be rated. Fig. 1 shows the use of the outage predictor within the base station-centered architecture.

In our analysis we classify the fading in two states, *up* and *outage*. An outage is defined as the event that the fading level falls below a specified threshold $|h_\mathrm{min}|$. When the fading is above the threshold $|h(t)| > |h_\mathrm{min}|$, we define the system to be in up state. Due to the probabilistic nature of channel coding, falling below the threshold $|h_\mathrm{min}|$ does not result in a sure packet error. Analogously, being above the threshold will also not guarantee a successful delivery. Therefore, the boundary line is not hard but rather blurred. In the up state packet errors occur only occasionally without long error bursts. For these remaining packet errors control systems could employ a robust controller design which can overcome a certain amount of consecutive packet errors [13]. The threshold value has to be chosen in a way that the remaining packet error probability in the up state, can be tolerated by the system.

III. Outage Predictor

To predict fading for future samples, we employ a Wiener filter, which belongs to the class of linear minimum mean square error (LMMSE) estimators. In the following we summarize the derivation of the Wiener filter fading predictor and the analysis of the prediction error from [7] before modifying it for outage prediction. For a prediction horizon t_p, the estimate of the future fading

$$\hat{h}(t + t_\mathrm{p} | \, t) = \boldsymbol{\varphi}(t) \boldsymbol{\Theta} \tag{5}$$

is the output of a finite impulse response (FIR) filter with coefficients $\boldsymbol{\Theta}$. The observation vector

$$\boldsymbol{\varphi}(t) = \big[\hat{h}(t) \quad \hat{h}(t - \Delta t) \quad ... \quad \hat{h}(t - (M-1)\Delta t)\big] \tag{6}$$

contains M past channel estimations with a fixed time between the observations Δt. The filter coefficients $\boldsymbol{\Theta}$ are calculated

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from the cross-covariance between fading and observations $\boldsymbol{r}_{h\varphi}$ and the autocovariance matrix $\boldsymbol{R}_{\varphi}$ of the observations

$$\boldsymbol{\Theta} = \boldsymbol{R}_{\varphi}^{-1}\boldsymbol{r}_{h\varphi} \quad . \tag{7}$$

Given the assumptions from (1) to (3), the missing variables to calculate the filter coefficients $\boldsymbol{\Theta}$ are found to be

$$[\boldsymbol{r}_{h\varphi}]_j = J_0(2\pi f_m(t_\mathrm{p} + (j-1)\Delta t)) \quad \text{and} \tag{8}$$

$$[\boldsymbol{R}_{\varphi}]_{ij} = \begin{cases} J_0(2\pi f_m|j-i|\Delta t) + 2\sigma_{n'}^2, & i \neq j \\ J_0(0) + 2\sigma_{n'}^2, & i = j \end{cases} \quad . \tag{9}$$

In order to utilize the predicted fading (5) for the detection of future outages, it is crucial to understand that a threshold different from $|h_\mathrm{min}|$ is required due to prediction errors. A predicted value, especially when it is close to the threshold $|h_\mathrm{min}|$, might in the worst case indicate an up state while the true future value of the fading is in outage. Such missed outages are highly problematic since the scheduler and the application might react too late. Therefore, a different threshold for the predicted value $|h'_\mathrm{min}| \geq |h_\mathrm{min}|$ needs to be chosen to predict outages more reliably. Thus, the proposed outage predictor consists of the predicted fading (5) and also a threshold value $|h'_\mathrm{min}|$. A future outage is indicated when the predicted fading $\hat{h}(t+t_\mathrm{p}|\, t)$ falls below the threshold $|h'_\mathrm{min}|$. Concurrently, the true future fading is predicted to be in the up state when the predicted fading $\hat{h}(t+t_\mathrm{p}|\, t)$ is above the threshold $|h'_\mathrm{min}|$.

A. Prediction error

For the given assumptions it can be shown, that the prediction error

$$e(t) = h(t+t_\mathrm{p}) - \hat{h}(t+t_\mathrm{p}|\, t) \tag{10}$$

follows a complex Gaussian distribution

$$\mathrm{Re}\{e(t)\},\, \mathrm{Im}\{e(t)\} \sim \mathcal{N}(\mu,\, \sigma^2) \quad . \tag{11}$$

This originates from both $h(t)$ and $\hat{h}(t+t_\mathrm{p}|\, t)$ being complex Gaussian distributed and therefore also their difference. Thus, the distribution of (10) is completely characterized by its first two moments. The bias of the prediction error $e(t)$ is determined according to

$$\mathbf{E}\big[\mathrm{Re}\{e(t)\}\big] = \mathbf{E}\big[\mathrm{Im}\{e(t)\}\big] = \mu = 0 \tag{12}$$

since a generally unbiased LMMSE estimator is employed. For the variance of the complex prediction error

$$\mathbf{E}\big[|e(t)|^2\big] = 1 - \boldsymbol{r}_{h\varphi}^\mathrm{T}\boldsymbol{R}_{\varphi}^{-1}\boldsymbol{r}_{h\varphi} \tag{13}$$

is obtained. With the variance of the real and imaginary parts of the prediction error

$$\mathbf{E}\big[\mathrm{Re}\{e(t)\}\big] = \mathbf{E}\big[\mathrm{Im}\{e(t)\}\big] = \sigma^2 = \frac{1}{2}\mathbf{E}\big[|e(t)|^2\big] \tag{14}$$

being half of the variance of the complex prediction error, since real and imaginary parts are identically distributed.

The accuracy of the outage predictor is based on the error standard deviation σ. Its value is determined by the Wiener filter parameters prediction length t_p, history length M and the time between observations Δt, as well as by external factors like receiver speed v and channel estimation signal-to-noise ratio (SNR). The prediction horizon t_p for scheduling purposes is the time difference between last channel observation and data transmission. For application warning purposes, the prediction horizon t_p needs to be chosen large enough that enough time is left for a reaction in case of an indicated outage, while too large prediction horizons result in a degradation of the estimation performance. The time between observations Δt is analyzed in Fig. 2. Here, the performance of the predictor against different sampling times for a fixed history length M and a constant channel estimation SNR is shown. In Fig. 2(b) it can be seen that very large as well as very small times between observations Δt are critical for the prediction performance. Very small times Δt for a fixed history length M result in the observation not spanning enough of the fading. Very large times Δt, which are greater than the coherence time of the channel, lead to observations which are almost uncorrelated. An optimal time between observations can be found for each curve, however, it is shown that any time between the optimum time and the coherence time of the channel can achieve a reasonable prediction performance (long plateau of σ). For lower average channel estimation SNR as shown in Fig. 2(a), the choice of Δt is more important as the curves have a well-defined minimum. In this case smaller times Δt are advantageous. The influence of channel estimation SNR and history length M are shown in Fig. 3 for a constant error standard deviation σ and a constant time between observations Δt. To achieve a certain predictor performance σ at a certain prediction horizon t_p, a trade-off between channel estimation SNR and history length M is possible. When not operating at the optimal time between observations Δt as depicted in Fig. 3(b) an increase of the history length M only results in small gains in terms of required channel estimation SNR. Higher values for M are beneficial when operating close to the optimal time between observations Δt, which is shown in Fig. 3(a).

B. Predicted Outage Probability

Knowing the distribution of the prediction error, a predicted fading value can now be associated with the probability for an outage. We denote the probability for a future outage given a certain predicted fading value $\hat{h}(t+t_\mathrm{p}|\, t)$ as $P(\text{future outage})$. As illustrated in Fig. 4, a future outage occurs when the prediction error $e(t)$ lies in the complex plane within an area A of a circle around $-\hat{h}(t+t_\mathrm{p}|\, t)$ with radius $|h_\mathrm{min}|$. This is because the sum of predicted fading value $\hat{h}(t+t_\mathrm{p}|\, t)$ and prediction error $e(t)$ is the true value of the future fading. For a prediction error within this circular area the true value of the fading lies within the outage region. Since the relationship between probability and probability density is described by an integral, $P(\text{future outage})$ is determined by a double integral over the area A according to

$$P(\text{future outage}) = \int_\mathrm{A} f_{\mathrm{Re}\{e\},\mathrm{Im}\{e\}}(x,y)\, d\mathrm{A} \quad . \tag{15}$$

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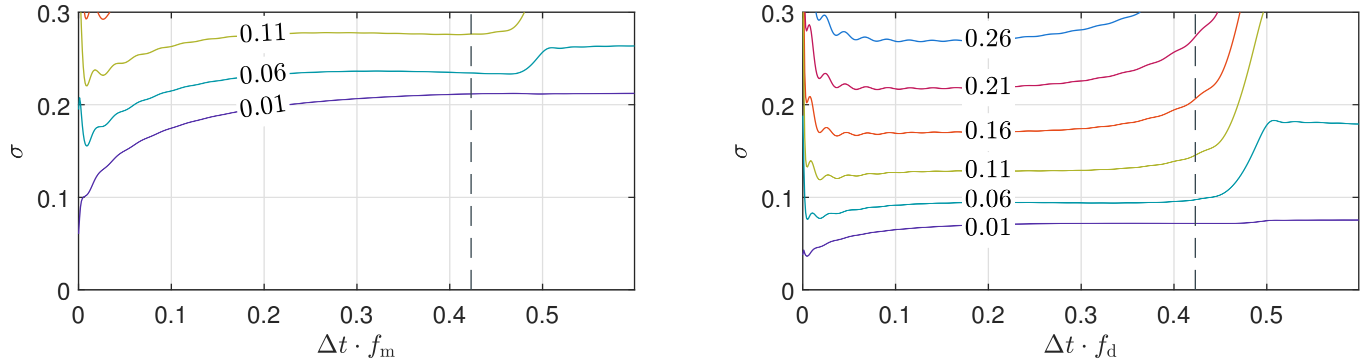
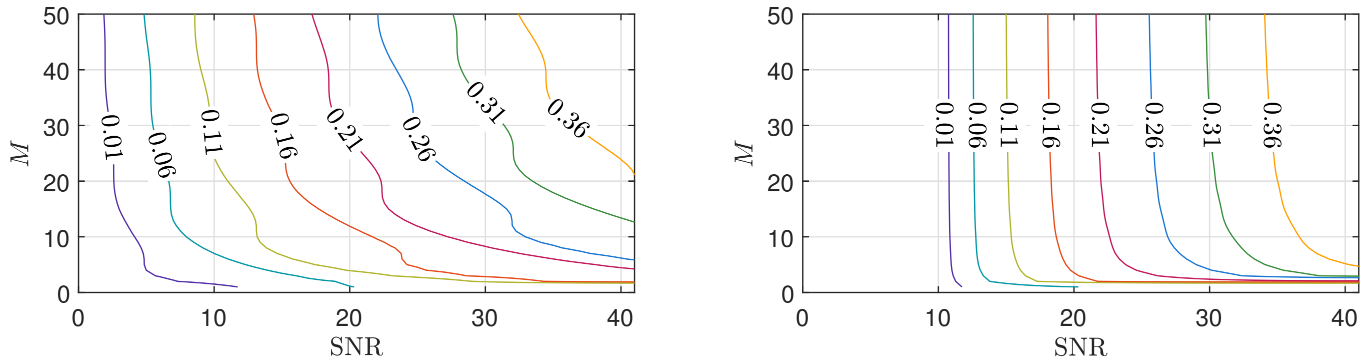


(a) SNR $= 10\,\mathrm{dB}$, $M = 20$

(b) SNR $= 20\,\mathrm{dB}$, $M = 20$

Fig. 2. Influence of the time between observations Δt on the predictor standard deviation σ, parameter of the family of curves is the normalized prediction horizon $t_\mathrm{p} \cdot f_\mathrm{m}$, dashed line is an empirical value for the coherence time [14].



(a) $\sigma = 0.2$, $\Delta t \cdot f_\mathrm{m} = 0.01$

(b) $\sigma = 0.2$, $\Delta t \cdot f_\mathrm{m} = 0.2$

Fig. 3. Trade-off between SNR and history length M to achieve a constant prediction performance, parameter of the family of curves is the normalized prediction horizon $t_\mathrm{p} \cdot f_\mathrm{m}$.

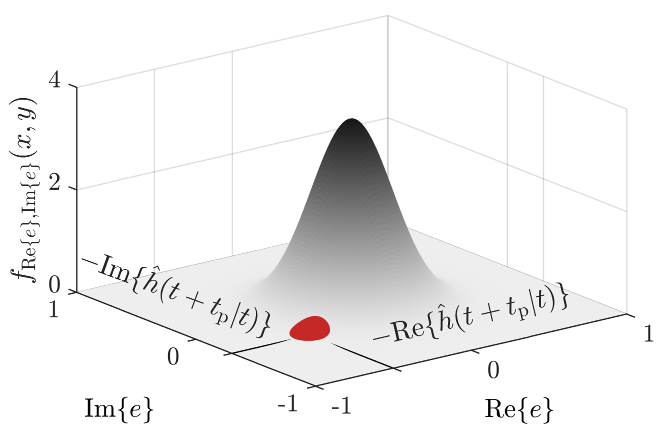


Fig. 4. Illustration of the future outage probability integration area, the red circle marks the integration area and has radius $|h_\mathrm{min}|$.

Here $f_{\mathrm{Re}\{e\},\mathrm{Im}\{e\}}(x, y)$ is the bivariate Gaussian probability density with mean μ and variance σ^2 for both dimensions. To the best of our knowledge no closed form solution is known for this integral. However, it can be evaluated numerically.

The predicted outage probability (15) can also be used to define the threshold value of the predicted fading $|h'_\mathrm{min}|$, if a maximum instantaneous tolerable outage probability can be specified. In Sec. V we will present an alternative way for the choice of $|h'_\mathrm{min}|$.

IV. Performance Metrics

An ideal predictor would be able to predict outages all the time the future fading truly is in outage, simultaneously indicating an up state in all other cases. Since in the presence of noise there are no black-and-white decisions, two kinds of errors occur.

The first error type refers to predicting an outage while no outage is going to take place. In these cases a radio resource scheduling algorithm utilizing the predictor rejects the channel without reason. We quantify this problem by means of the probability to find a channel to be predicted as up $P(\text{predicted up})$. This probability indicates how often a channel is considered up by the scheduler and therefore utilized for URLLC traffic on average. The more outages are predicted while the fading truly is up, the lower $P(\text{predicted up})$ gets.

The second error type, which is more critical in the context of this work, happens when the predictor misses an outage

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TABLE I
CHOSEN PARAMETERS FOR NUMERICAL EVALUATION.

Parameter	Value
v	$1\,\mathrm{m/s}$
f_c	$3.75\,\mathrm{GHz}$
channel estimation SNR	$20\,\mathrm{dB}$
minimal decodable SNR	$10\,\mathrm{dB}$
M	25
Δt	$1\,\mathrm{m/s}$
number of repetitions	up to 3.5×10^{10}

by indicating an up state even though the true value of the future fading lies in outage. This type of error is also denoted as a miss and the QoS of an URLLC system utilizing the outage predictor is mainly determined by the probability of this error. The compound probability for a predicted up and the channel being truly in outage, which we use for quantification, is denoted as $P(\text{missed outage})$ in the following.

V. NUMERICAL EVALUATION

In this section, we evaluate the performance of the proposed outage predictor. In general, the standard deviation of the predictor σ and the relation between the channel estimation SNR value and the minimal decodable SNR value fully define the outage prediction performance for Rayleigh fading channels. For better understanding, the evaluation in this section is shown for an exemplary scenario and selected numeric values. We consider an industrial setting where an AGV is controlled wirelessly. The assumed numerical values are conducted in Table I. We consider the AGV to be driving with a constant speed of $v = 1\,\mathrm{m/s}$, which is common for such vehicles. The communications system is considered to be operating in the frequency band $3.7\,\mathrm{GHz}$ to $3.8\,\mathrm{GHz}$, which was allocated for wireless industrial communications in Germany recently. The utilized carrier frequency $f_\mathrm{c} = 3.75\,\mathrm{GHz}$ is in the middle of this frequency band. Furthermore, the radio channel estimation is characterized by its mean SNR value of $20\,\mathrm{dB}$ and we define a minimal tolerable SNR value $\mathrm{SNR}_\mathrm{min} = 10\,\mathrm{dB}$. The predictor uses the past $M = 25$ samples for prediction and is expecting samples every $\Delta t = 1\,\mathrm{ms}$. However, as discussed in Sec. III-A, also sampling times up to the coherence time (for this scenario around $330\,\mathrm{ms}$) can achieve a similar performance for the same prediction horizons t_p.

The results in this section are generated by means of computer simulation utilizing the Monte-Carlo approach. Up to $3.5 \cdot 10^{10}$ noisy Rayleigh fading channel estimations $\hat{h}(t)$ are generated and used as input for the Wiener filter (5). For multiple prediction horizons and the whole range of possible prediction thresholds $|h'_\mathrm{min}|$, the up states and outages of the randomly generated fading are predicted. The predicted outages are then compared with the true state of the fading sequence, which is determined by using the time shifted non-noisy Rayleigh fading $h(t + t_{t_\mathrm{p}})$ and the outage threshold $|h_\mathrm{min}|$. The probabilities $P(\text{predicted up})$ and $P(\text{missed outage})$ are then empirically approximated following the law of large numbers.

The prediction performance for the chosen parameters is shown in Fig. 5(a). The curves represent the performance of the predictor for different prediction horizons t_p. Each line spans different operating points, which can be adjusted by varying the threshold for the predicted fading $|h'_\mathrm{min}|$. If, for instance, a communications resource scheduler needs $1\,\mathrm{ms}$ to assign or switch resources after the last training signal is received, a prediction horizon of $1\,\mathrm{ms}$ would be utilized. The target probability for a missed outage $P(\text{missed outage})$ could be set to 10^{-3}, which reduces the probability for an outage on this link by factor 100 compared to best effort transmissions without prediction. The average probability that this link is considered to be in the up state and therefore utilized is then $87\,\%$. When a much larger prediction horizon of $21\,\mathrm{ms}$ is considered the same probability for a missed outage $P(\text{missed outage}) = 10^{-3}$ can be achieved, but the channel will in this case be predicted as up only $40\,\%$ of the time. The curves shown here demonstrate the prediction performance only for a single channel. In a scheduling system multiple channels would be monitored in parallel. The question which minimal probability for finding each of these channels to be predicted as up becomes a scheduling problem and is not part of this paper.

Fig. 5(b) shows an alternate way for the choice of the threshold $|h'_\mathrm{min}|$ compared to Sec. III-B. Here a target probability for a missed outage $P(\text{missed outage})$ has to be given, which is the case when an average link performance is targeted. The previously discussed values are achieved utilizing threshold values of $|h'_\mathrm{min}| = 0.37$ and $|h'_\mathrm{min}| = 0.88$, respectively.

VI. CONCLUSION

Fading prediction methods are capable of saving communications resources by scheduling users to resources that are predicted to have sufficiently good link quality. Resources that are in outage for a specific UE are not considered as candidates for transmission, instead may be operable for another UE due to the spatial variation of fast fading. The proposed outage predictor extends existing fading prediction methods [7] due to its capabilities of achieving specific prediction certainties, making it a promising candidate for URLLC implementations. The predictor achieves a good performance in Rayleigh fading channels even with only a few observed fading samples available. Furthermore, the predictor is able to successfully operate over a wide range of sampling intervals for the observations. From our numerical evaluation we conclude that the proposed outage predictor has the potential to reduce the probability of an outage on a single link by orders of magnitude. Simultaneously, the predictor indicates an up state for channels which

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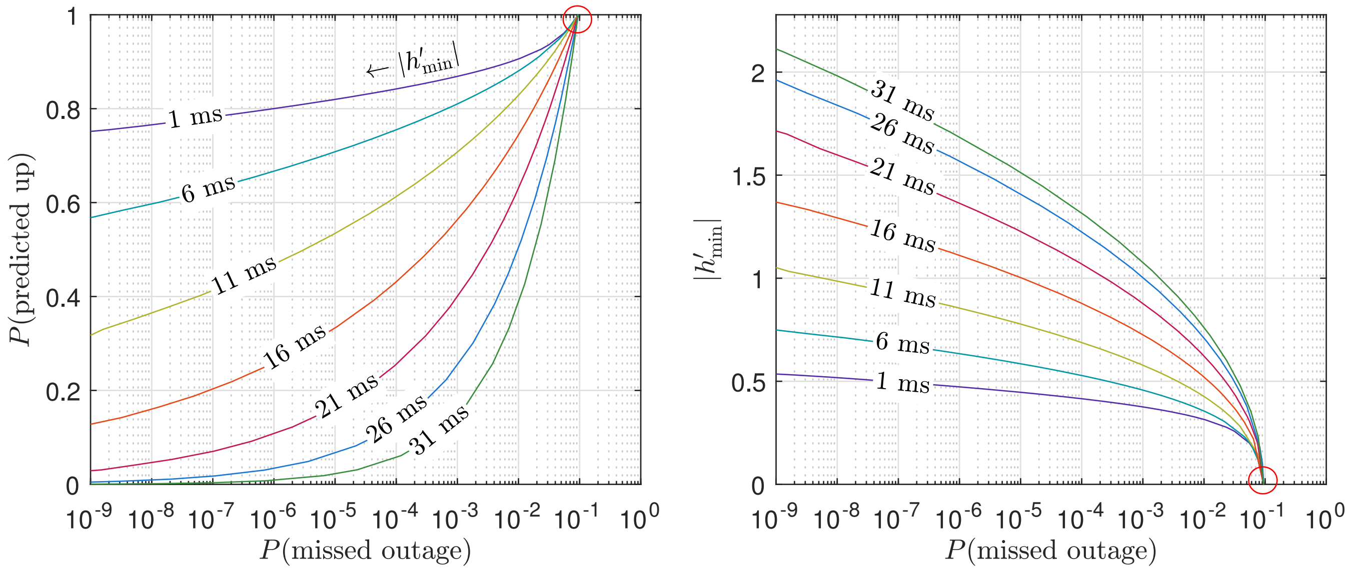

(a) operating curves

(b) choice of the operating point by varying $|h'_{\min}|$

Fig. 5. Predictor performance for $\mathrm{SNR}_{\min} = 10\,\mathrm{dB}$, $\mathrm{SNR} = 20\,\mathrm{dB}$, $f_c = 3.75\,\mathrm{GHz}$, $v = 1\,\mathrm{m/s}$, $\Delta t = 1\,\mathrm{ms}$, $M = 25$, parameter of the family of curves is the prediction horizon t_p, the red circle marks the single link performance without prediction.

are truly up reasonably well for short prediction horizons of some milliseconds and for slowly varying channels. In faster changing environments or when long prediction horizons are needed, the performance decreases rapidly, requiring fall back methods for URLLC, e.g., classical diversity methods. It is left for future work to study how the outage prediction performance develops under real world conditions, when the correlation of the channel has to be estimated. Also, the development of a scheduler that is able to exploit the additional information gathered from the predictor is left for future work.

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