Toward Practical Anticipatory Video Delivery for the Internet-of-Vehicles

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***Abstract*—Today deployments of massive Internet of Things (IoT) applications are expected from 5G networks. A primary challenge however is designing *scalable* wireless resource management schemes that can adapt to the varying temporal and spatial demand of IoT applications. As such, intelligence-based solutions that are agile to, and are able to *exploit* IoT traffic patterns are emerging as key enablers for 5G IoT applications. For example, Predictive Resource Allocation (PRA) has been proposed in wireless network literature as a mechanism to provide significant energy-savings and Quality of Experience (QoE) gains by leveraging predictions of the user location. While the results are very promising, further research is needed to 1) model and handle the inherent uncertainty in the predicted rates of PRA, and 2) develop low-complexity solutions for practical adoption. This is the topic of this paper, where we present a credibility-based chance-constrained fuzzy programming solution for PRA that enables the operator to control the energy efficiency-QoE tradeoff for different users and services. We demonstrate the use of a Kalman Filter (KF) to adaptively model rate prediction uncertainty by modifing the limits of the fuzzy membership functions in real-time. Our simulation results indicate that the proposed credibility-based framework provides a low-complexity solution for robust PRA.**

I. Introduction

Next generation 5G networks and beyond are anticipated to transform modern societies by providing an ultra-reliable, high speed communications infrastructure that will serve smart city applications such as industrial automation and connected and autonomous vehicles. However, providing *scalable* cost-efficient deployments of "Internet of Things" based services remains to be a primary challenge operators and network vendors are facing. As such, intelligence-based, context-aware and predictive solutions that are able to *exploit* IoT traffic patterns are emerging as key enablers for the 5G era of IoT applications. The key requirements however for practical adoption are low-complexity and flexibility since the majority of "machine learning" and stochastic optimization based solutions are too complex for imminent industrial implementations.

The high predictability of user mobility, traffic patterns and wireless channel quality has enabled a promising energy-efficient QoS-aware radio resource management paradigm referred to as Predictive Resource Allocation (PRA) [1]–[3]. It has been shown that the radio signal strength and availability of radio resources typically follow repetitive spatio-temporal patterns [4] which can be used to anticipate the future radio conditions. PRA leverages these forecasts of user demands over an upcoming time-horizon to strategically decide the best time period to deliver large chunks of data, and identify the durations in which the base station can abandon data transmission and go into energy saving mode [1], [2]. One of the main challenges facing PRA is the uncertainties associated with the future information. As such, robust techniques that model the uncertainty in predicted information are of paramount importance to deliver a reliable QoE.

In this paper, we propose a fuzzy-based optimization model that tackles uncertainty in network constraints and thus provides robust decisions that satisfies the application's QoS under typical prediction error models. We summarize the main contributions of this paper in the following:

- We show how the uncertainty in the predicted channel capacity can be modelled using fuzzy trapezoidal numbers. The models are compared to standard compliant transport block sizes using an LTE simulator.
- We apply fuzzy credibility theory to perform robust long term predictive resource allocation within a certain degree of user satisfaction. The fuzzy approach provides a low complexity based solution to the chance-constrained programming problem of PRA.
- We periodically measure the degree of uncertainty in the rate predictions and use this feedback to modify the fuzzy trapezoidal membership functions in real-time. This is achieved via Kalman Filter (KF) based tracking during the time horizon. A thorough performance analysis is provided to illustrate the interaction between the adaptive models and the credibility-based PRA solution.

In the next section we present more details on PRA and discuss the use of credibility based fuzzy optimization to model uncertainty. Details of the proposed credibility-based chance constrained PRA are presented in Section IV, and the KF approach to track the level of uncertainty in Section V. A thorough performance evaluation is made in Section VI, followed with our conclusions in Section VII.

II. Background & Related Work

A. Predictive Resource Allocation

PRA exploits repetitive patterns of signal strength and mobility prediction over a time horizon to calculate the future channel conditions that will be experienced by a mobile device. Based on these calculated values, the resource allocation plan is created, which incorporates delivering the

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future content ahead of time or postponing the data delivery until network conditions are improved [1]–[3]. To quantify the potential performance gains over non-predictive schemes, research in PRA typically assumes perfect prediction of future channel rates and network conditions.

However, despite their high predictability, estimated channel and mobility are typically prone to errors over time horizon due to location prediction errors and uncertainty in the radio environment maps due to varying interference levels and small scale fading associated with the wireless signal [4]. Modeling uncertainty and incorporating robustness in PRA has therefore been considered in some previous work [5], [6]. Our prior work in [5] tackled the problem from a stochastic optimization approach, our work in [6] modelled the uncertain future channel rate as a triangular fuzzy number and adopted α-cut method to obtain a closed-form linear programming model. An unresolved challenge in fuzzy optimization is the conservative nature of constraint over-satisfaction which we address in this paper by using chance-constrainted programming and and KF adaptive tracking to estimate the channel variance.

B. Credibility-Based Fuzzy Optimization

In fuzzy optimization, uncertain variables and coefficients in constraints or objective functions are represented as fuzzy numbers. This results in a chance constraint programming (CCP) model or multi-stage fuzzy programming problem [7]. The membership function represents the range of uncertainty and possible outcomes for each uncertain coefficient. In the CCP, the constraints of the optimization model have to be satisfied by a certain predefined level that strikes a balance between violating the design requirements and achieving the global objective. A crisp model is then typically derived to obtain a closed-form deterministic equivalent model for the CCP. This can be done by using different measures such as possibility [8], it's dual necessity, or the self-dual credibility which is the average of the former two measures [9]. Due to it's self-duality, the credibility measure is used to represent the expected value of a fuzzy programming model and can also be used as a probabilistic measure which best describes the chance of satisfying the fuzzy constraint [9]. Credibility measures have been applied in different applications such as in portfolio selection [10] to control the investment risk, and network routing [11] to guarantee the packet delay constraint.

In this paper we apply the credibility measure to obtain the crisp deterministic form of the chance constraint that represents the user quality of service (QoS). In particular, the main source of uncertainty is assumed to be the predicted channel rate which is represented as a fuzzy number with a trapezoidal membership. The fuzzy constraint represents the chance of meeting the user demand by the allocated radio resources at a certain time slot is above a minimal satisfaction degree representing the target QoS level of the user.

III. System Model

We use the following notational conventions: $\mathcal{X}$ denotes a set and it's cardinality is denoted by X. Matrices are denoted with subscripts, e.g. $\mathbf{x} = (x_{a,b} : a \in \mathbb{Z}_+, b \in \mathbb{Z}_+)$.

A. Overview

The system is comprised of a wireless Base Station (BS) with an active user set denoted by $\mathcal{M}$, where each mobile user is denoted by $i \in \mathcal{M}$. The system applies predictive allocation to the set of users $\mathcal{M}$ that request stored video content which is transported over HTTP as a progressive download. The core network bandwidth is set to 1 Gbps and the video content is assumed to be accessible at the BS. The main source of uncertainty is the predicted channel rates resulting from varying interference or inaccurate estimations of user locations. We define the prediction window as the part of the time horizon in which the users' locations are known for the upcoming T seconds at a per second granularity. From the above information, a matrix of the average values of future user rates, defined by $\hat{\mathbf{r}} = (\hat{r}_{i,t} : i \in \mathcal{M}, t \in \mathcal{T})$ is computed. The values in this matrix will then be fuzzified to account for uncertainty according to the model presented in Section V-A1.

B. Resource Sharing and Scheduling

The BS airtime is assumed to be the radio resources that are divided among the active users at each time slot t. We define the resource allocation matrix $\mathbf{x} = (x_{i,t} \in [0,1] : i \in \mathcal{M}, t \in \mathcal{T})$ which computes the fraction of time during each slot t that the BS bandwidth is assigned to user i. Airtime sharing is implemented as a time division rate controller on top of the Round-robin (RR) scheduler in ns-3.

C. Deterministic Predictive Video Delivery

The goal of predictive resource allocation for video streaming is to opportunistically deliver content in advance to the User Equipment (UE) during favorable radio conditions - and thereafter suspend transmission while the user consumes the buffer. Mathematically, this can be formulated as follows. If we consider resource allocation over discrete time slot durations of one second, and the user is requesting a video stream at rate of V [bit/s], then the minimum cumulative video content for smooth streaming is $D_{i,t} = V \cdot t$. Also, let us denote the cumulative allocation made to a user i by slot t by $A_{i,t} = \sum_{t_1=1}^{t} x_{i,t_1} \hat{r}_{i,t_1}$. To prevent video freezes, the PRA should ensure that $A_{i,t} \geq D_{i,t} \, \forall \, t$ for user i. The optimization problem can be formulated as the following Linear Program (LP) [6]:

$$
\begin{aligned}
\underset{\mathbf{x}}{\text{minimize}} \quad & \sum_{t=1}^{T} \sum_{i=1}^{M} x_{i,t} && && (1) \\
\text{subject to:} \quad & \text{C1:} \quad D_{i,t} - A_{i,t} \leq 0, && \forall \, i \in \mathcal{M}, t \in \mathcal{T}, \\
& \text{C2:} \quad \sum_{i=1}^{M} x_{i,t} \leq 1, && \forall t \in \mathcal{T}, \\
& \text{C3:} \quad x_{i,t} \geq 0 && \forall \, i \in \mathcal{M}, t \in \mathcal{T}.
\end{aligned}
$$

The solution of Eq. 1 will not cause streaming discontinuities only if the predicted rates are accurate. However, if the actual rate happens to be less than the predicted rate, the user will suffer from video stalls. On the other hand, a prebuffering opportunity is considered lost if the actual rate is larger than what was predicted. To capture and adapt to such variations, we present a credibility-based robust PRA framework in the following section.

IV. Credibility-Based Predictive RA

A. Background: The Credibility Measure

The credibility measure for fuzzy numbers was first introduced in [12] as the average of both the possibility and necessity measures as follows:

$$Pos\{\xi \geq r\} = \sup_{u \geq r} \mu_{\xi}(u) \tag{2}$$

$$Nec\{\xi \geq r\} = 1 - \sup_{u < r} \mu_{\xi}(u) \tag{3}$$

$$Cr\{\xi \geq r\} = \frac{1}{2}(Pos\{\xi \geq r\} + Nec\{\xi \geq r\}) \tag{4}$$

Similarly,

$$Cr\{\xi \leq r\} = \frac{1}{2}(Pos\{\xi \leq r\} + Nec\{\xi \leq r\}) \tag{5}$$

Where ξ is a fuzzy number with membership function $\mu_{\xi}\{.\}$ and r is a crisp threshold value. The notations for possibility, necessity and credibility are Pos, Nec, and Cr respectively.

B. Problem Formulation

The credibility based robust formulation of the optimization problem described in Section III-C can be expressed as follows:

$$\underset{\mathbf{x}}{\text{minimize}} \quad \sum_{t=1}^{T} \sum_{i=1}^{M} x_{i,t} \tag{6}$$

$$\begin{aligned}
\text{subject to:} \quad & \text{C1:} \quad Cr\left\{\sum_{t'=0}^{t} \tilde{r}_{i,t} x_{i,t} \geq D_{i,t}\right\} \geq \beta, \forall i \in \mathcal{M}, t \in \mathcal{T}, \\
& \text{C2:} \quad \sum_{i=1}^{M} x_{i,t} \leq 1, \forall t \in \mathcal{T}, \\
& \text{C3:} \quad x_{i,t} \geq 0 \quad \forall i \in \mathcal{M}, t \in \mathcal{T}.
\end{aligned}$$

The above credibility formulation is converted to its deterministic equivalent based on the membership function of the fuzzy number $\tilde{r}_{i,t}$, and is shown in Fig. 1. In this paper we investigate how to model rate uncertainty using the credibility measure for trapezoidal fuzzy numbers due to their suitability in modeling the discrete levels of wireless transport block sizes as demonstrated in Fig. 2 and Fig. 3.

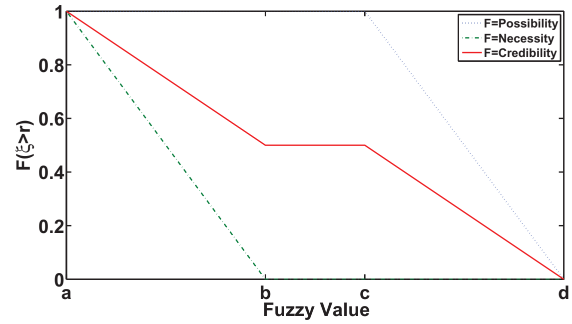

Fig. 1. Different membership representations for Fuzzy Rate R.

C. Trapezoidal Fuzzy Number Representation

In this section we assume the fuzzy number $\tilde{r}_{i,t}$ has a trapezoidal membership function $\mu_{\tilde{r}_{i,t}} = (r_{i,t}^{LL}, r_{i,t}^{LU}, r_{i,t}^{UL}, r_{i,t}^{UU})$. The possibility, necessity and credibility measures of constraint (C1) in Eq. 6 can be expressed as:

$$Pos\{\tilde{r}_{i,t} \geq D_{i,t}\} = \begin{cases} 1, & D_{i,t} \leq \tilde{r}_{i,t}^{LL} \\ 1, & \tilde{r}_{i,t}^{LL} < D_{i,t} \leq \tilde{r}_{i,t}^{LU} \\ 1, & \tilde{r}_{i,t}^{LU} < D_{i,t} \leq \tilde{r}_{i,t}^{UL} \\ \frac{D_{i,t} - r_{i,t}^{UU}}{r_{i,t}^{UL} - r_{i,t}^{UU}}, & \tilde{r}_{i,t}^{UL} < D_{i,t} \leq \tilde{r}_{i,t}^{UU} \\ 0, & D_{i,t} > \tilde{r}_{i,t}^{UU} \end{cases} \tag{7}$$

$$Nec\{\tilde{r}_{i,t} \geq D_{i,t}\} = \begin{cases} 1, & D_{i,t} \leq \tilde{r}_{i,t}^{LL} \\ 1 - \frac{D_{i,t} - r_{i,t}^{LL}}{r_{i,t}^{LU} - r_{i,t}^{LL}}, & \tilde{r}_{i,t}^{LL} < D_{i,t} \leq \tilde{r}_{i,t}^{LU} \\ 0, & \tilde{r}_{i,t}^{LU} < D_{i,t} \leq \tilde{r}_{i,t}^{UL} \\ 0, & \tilde{r}_{i,t}^{UL} < D_{i,t} \leq \tilde{r}_{i,t}^{UU} \\ 0, & D_{i,t} > \tilde{r}_{i,t}^{UU} \end{cases} \tag{8}$$

$$Cr\{\tilde{r}_{i,t} \geq D_{i,t}\} = \begin{cases} 1, & D_{i,t} \leq \tilde{r}_{i,t}^{LL} \\ \frac{1}{2}(2 - \frac{D_{i,t} - r_{i,t}^{LL}}{r_{i,t}^{LU} - r_{i,t}^{LL}}), & \tilde{r}_{i,t}^{LL} < D_{i,t} \leq \tilde{r}_{i,t}^{LU} \\ \frac{1}{2}, & \tilde{r}_{i,t}^{LU} < D_{i,t} \leq \tilde{r}_{i,t}^{UL} \\ \frac{1}{2}\frac{D_{i,t} - r_{i,t}^{UU}}{r_{i,t}^{UL} - r_{i,t}^{UU}}, & \tilde{r}_{i,t}^{UL} < D_{i,t} \leq \tilde{r}_{i,t}^{UU} \\ 0, & D_{i,t} > \tilde{r}_{i,t}^{UU} \end{cases} \tag{9}$$

Consequently, the deterministic equivalent of $Cr\{\tilde{r}_{i,t} \geq D_{i,t}\} \geq \beta$ depends on the value of constraint satisfaction degree β as follows [13]:

- $\beta \leq 0.5$

$$Cr\{\tilde{r}_{i,t} \geq D_{i,t}\} = \frac{1}{2}\frac{D_{i,t} - r_{i,t}^{UU}}{r_{i,t}^{UL} - r_{i,t}^{UU}} \tag{10}$$

which corresponds to the region $D_{i,t} > r_{i,t}^{UL}$. Therefore,

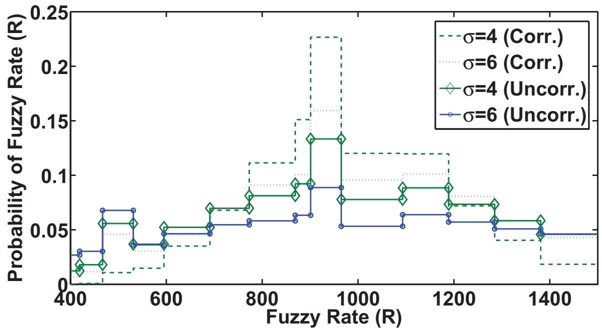

Fig. 2. Simulated variations of predicted rate = 901 due to Gaussian distribution shadowing with different variances σ.

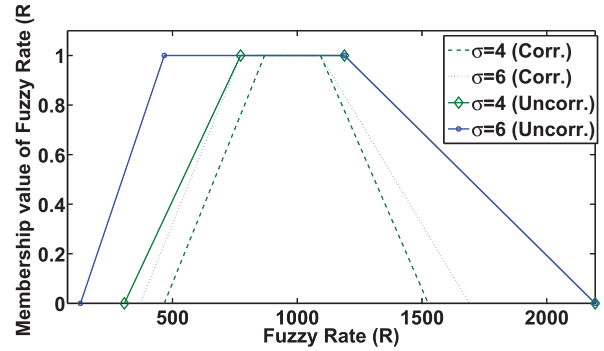

Fig. 3. Trapezoidal membership function of the predicted fuzzy rate = 901 due to both correlated and uncorrelated gaussian distribution shadowing with different variances σ.

$$\frac{1}{2}\frac{D_{i,t} - r_{i,t}^{UU}}{r_{i,t}^{UL} - r_{i,t}^{UU}} \geq \beta \tag{11}$$

$$D_{i,t} \leq 2\beta\ r_{i,t}^{UL} + (1-2\beta) r_{i,t}^{UU} \tag{12}$$

Finally, the total deterministic equivalent of the credibility constraint will be:

$$\text{C1:}\quad \sum_{t'=0}^{t} (2\beta\ r_{i,t}^{UL} + (1-2\beta) r_{i,t}^{UU})\ x_{i,t} \geq D_{i,t}, \forall i \in \mathcal{M}, t \in \mathcal{T}, \tag{13}$$

- $\beta > 0.5$

$$Cr\left\{\tilde{r}_{i,t} \geq D_{i,t}\right\} = \frac{1}{2}(2 - \frac{D_{i,t} - r_{i,t}^{LL}}{r_{i,t}^{LU} - r_{i,t}^{LL}}) \tag{14}$$

which corresponds to the region $D_{i,t} \leq r_{i,t}^{UL}$.
Therefore,

$$\frac{1}{2}(2 - \frac{D_{i,t} - r_{i,t}^{LL}}{r_{i,t}^{LU} - r_{i,t}^{LL}}) \geq \beta \tag{15}$$

$$D_{i,t} \leq (2\beta - 1)\ r_{i,t}^{LL} + (2 - 2\beta) r_{i,t}^{LU} \tag{16}$$

Finally, the total deterministic equivalent of the credibility based chance constraint will be:

$$\text{C1:}\quad \sum_{t'=0}^{t} ((2\beta-1)\ r_{i,t}^{LL} + (2-2\beta) r_{i,t}^{LU})\ x_{i,t} \geq D_{i,t}, \forall i \in \mathcal{M}, t \in \mathcal{T}, \tag{17}$$

V. Adaptive Uncertainty Modeling

A. Fuzzifier: Modeling Rate Uncertainty

1) Rate Membership Function: We represented the fuzzy predicted rate $\tilde{r}_{i,t}$ by either a triangular or a trapezoidal membership function. The $r_{i,t}^{UU}$ right and left $r_{i,t}^{LL}$ most points on the x-axis define the limits of the trapezium‘s or triangle's base, which physically represent the boundaries on the variation of the predicted rate $\hat{r}$.

2) Defining the Degree of Rate Uncertainty: Unlike the traditional approaches of credibility-based optimization, we adapt the membership function using the estimated degree of rate variations which is represented by the uncertainty factor α. As such, when the users are located in dynamic environment with large channel variations due to high mobility or poor prediction, the actual rate will experience wide variations from the predicted value. This requires a membership function with larger bounds that guides the resource allocator to provide more conservative solutions. Where these larger bounds are achieved by adopting a small value of α. On the contrary, a high value of α represents a relatively stable channel and more accurate prediction that result in small rate deviations. Thus, a narrower membership function can be used to maximize the energy-saving by allocating smaller airtime to users in poor radio conditions.

B. Credibility-Based Chance Constraint for Robust PRA

The fuzzy representation of the cumulative constraint is as follows

$$\tilde{\text{C1}}:\quad D_{i,t} - \sum_{t_1=1}^{t} \tilde{r}_{i,t_1} x_{i,t_1} \leq 0, \qquad \forall i \in \mathcal{M}, t \in \mathcal{T}. \tag{18}$$

According to IV-C and using the general form of the credibility measure, the fuzzy constraint Eq. (18) is expressed as:

$$\tilde{\text{C1}}:\quad Cr\left\{\sum_{t_1=1}^{t} \tilde{r}_{i,t_1} x_{i,t_1} \geq D_{i,t}\right\} \geq \beta, \qquad \forall i \in \mathcal{M}, t \in \mathcal{T}. \tag{19}$$

and its deterministic crisp equivalent for a reliable QoS $\beta \geq 0.5$ is:

$$\text{C1:}\quad \sum_{t'=0}^{t} ((2\beta - 1)\ r_{i,t}^{LL} + (2 - 2\beta) r_{i,t}^{LU})\ x_{i,t} \geq D_{i,t}, \tag{20}$$

C. Adaptive α-Tuning: Tracking Rate Variability

Extensive measurements showed that the level of error in the predicted channel rates varies over time and location [4]. As such, adopting a constant membership function will result in 1) conservative solution that compromises the prediction gains when the estimation is accurate; and 2) non- robust decisions that violate the QoS level if the prediction error is high

To that extent, we adopt KF to track the level of uncertainty in the predicted information using periodic channel measurements and then calculate the uncertainty factor α which adapts the bounds of the membership function.

1) Kalman Filter based Uncertainty Estimation: We define the KF state as the degree of uncertainty $\delta_{i,t}$ which represents the degree of uncertainty in the predicted rate. The state is updated using the measurement value $Z_{i,t} = \bar{\delta}_{i,t}$:

$$Z_{i,t} = \bar{\delta}_{i,t} = \frac{|\bar{r}_{i,t-1} - \hat{r}_{i,t-1}|}{\max(\bar{r}_{i,t-1}, \hat{r}_{i,t-1})}, \tag{21}$$

$$\delta^{+}_{i,t} = \delta^{-}_{i,t} + K(\bar{\delta}_{i,t} - \delta^{-}_{i,t}) \tag{22}$$

where $\hat{r}_{i,t-1}$ is the predicted channel capacity, $\bar{r}_{i,t-1}$ is the actual rate measured by the user in the previous time slot, and K is the Kalman filter gain. $\delta^{-}_{i,t}$ and $\delta^{+}_{i,t}$ correspond to the priori and posteriori state estimates. The details of our KF implementation can be found in [6].

2) α-Tuning Utility: The KF estimated posterior degree of uncertainty δ is then used to calculate the uncertainty factor α at time slot t using the below utility function:

$$\alpha_t = 1 - e^{-\gamma/|\delta_{i,t}{}^{+}|}, \tag{23}$$

This function drives the uncertainty factor α to 1 as the uncertainty approaches 0 (i.e., the predicted and measured rates are equal), and vice versa. The left handside of the QoS constraint Eq. 20 is then multiplied by α to scale the bounds of the uncertain rate based on the measured uncertainty level.

VI. Performance Evaluation

A. Simulation Set-up and Metrics

The credibility-based PRA is evaluated by simulating an LTE network using the Network Simulator (ns-3) with a a highway mobility scenario. To solve the deterministic equivalent of the credibility-based PRA optimization problem (in Eq. 20 we have integrated the Gurobi solver into the simulator.

Video quality is captured by measuring the percentage of video stops (or buffer underruns) that users experience, referred to as VD. The average BS airtime used to transmit the video to all the users is the second metric. We investigate the performance of the credibility-based PRA under the following system setup and model variations:

- Various settings of fixed rate uncertainty, and the KF adaptive rate uncertainty.
- Degree of constraint satisfaction (0.75 and 1).
- Various degrees of channel error variances (2 and 6).

B. Simulation Results

1) Degree of Uncertainty and KF Tracking: In Fig. 4(a) we illustrate the performance of the trapezoidal fuzzy membership function under various degrees of uncertainty, and a target constraint satisfaction rate $\beta = 0.75$. The the confidence intervals of 0.95 are included in the plots to indicate the degree of certainty in the achieved metrics. As shown the value of α dictates the trade-off between constraint satisfaction (i.e., the average video degradation), and the consumed BS airtime. For instance, an $\alpha = 0$ guarantees minimal VD but results in a very high airtime. The figure also shows the trade-off achieved by the KF based approach of dynamically adapting α based on the current rate prediction uncertainty. We can observe that this adaptive approach provides a better VD-airtime trade-off than the pareto-optimal achievable via a fixed α. This approach of adaptive the degree of rate uncertainty dynamically is particularly useful in practical systems where channel variations are typically due to bursty interference from neighboring transmissions,

2) Degree of Constraint Satisfaction: Fig. 4(b) illustrates the effect of increasing the degree of constraint satisfaction from 0.75 to 1. As expected the airtime increases considerably, particularly for the most conservative case where $\alpha = 0$. The reduction of the VD is also clear for the intermediate cases of $\alpha = 0.5, 0.75$ where being stricter with the target degree of constraint satisfaction improves the VD metric. The performance of the KF based α tracking is also impacted by the constraint satisfaction setting in terms of airtime increase but the VD is already low in this scenario, so it is not affected.

3) Effect of the Error Variance: The impact of the variance in the predicted error is investigated next. We repeat the same simulations while increasing the predicted rate error variance σ from 2 to 6 in Fig. 5. Here we observe the increase in VD for all the degrees of uncertainty and constraint satisfaction levels. The airtime confidence interval is also high due to the high channel variability which can result in either bursty highs or lows during each simulation. We note that the effectively of the KF to track the rate uncertainty in such scenarios decreases particularly when $\beta = 0.75$. As such under high channel variance it is recommended to apply a higher degree of constraint satisfaction to achieve reliable performance.

VII. Conclusion

Incorporating intelligence in wireless networks is paramount to enabling scalable IoT deployments where the networks adapt to the varying spatial and temporal traffic patterns. In this paper we present a credibility-based chance-constrained fuzzy programming solution for PRA under uncertainty. The proposed solution was applied for energy-efficient resource allocation of video streams using a standard compliant LTE system to investigate the performance of the proposed solutions under various environmental conditions. The effectiveness of the KF to track uncertainty and modify the limits of the fuzzy membership functions in real-time was demonstrated. The KF provided a mechanism to meet the QoE constraints, while significantly reducing BS energy. Our results indicate that the proposed credibility-based fuzzy programming model provides a low-complexity solution to incorporating uncertainty in predictive resource allocation.

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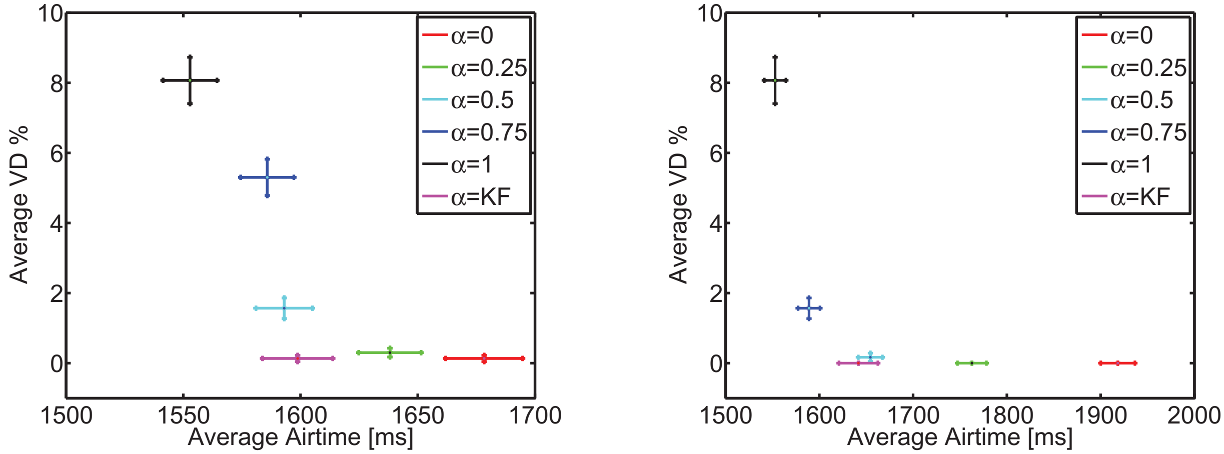
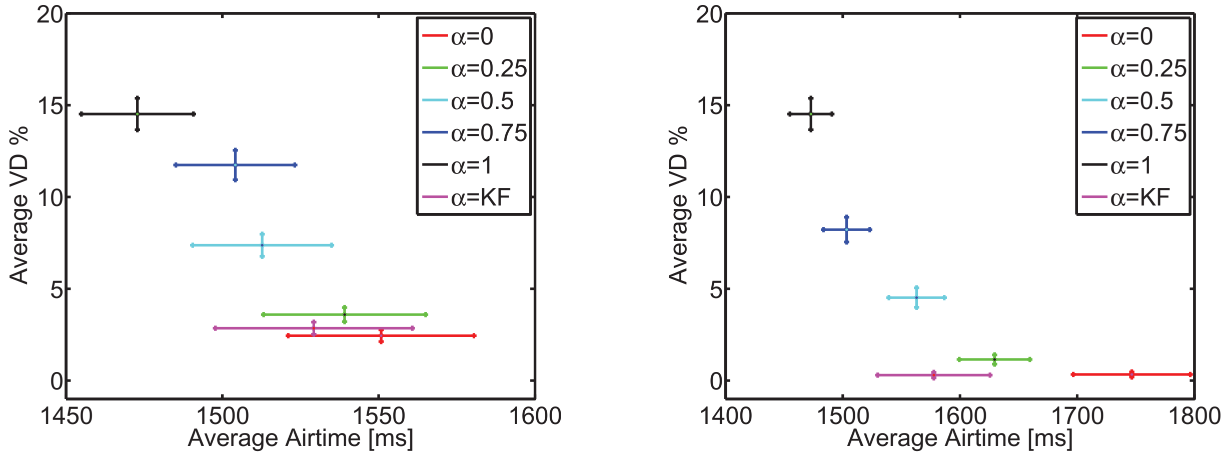


(a) Degree of Constraint Satisfaction $\beta = 0.75$. (b) Degree of Constraint Satisfaction $\beta = 1$.

Fig. 4. VD and average BS airtime for different degrees of uncertainty α under uncorrelated error with variance $\sigma = 2$ (trapezoidal membership function).



(a) Degree of Constraint Satisfaction $\beta = 0.75$. (b) Degree of Constraint Satisfaction $\beta = 1$.

Fig. 5. VD and average BS airtime for different degrees of uncertainty α under uncorrelated error with variance $\sigma = 6$. (trapezoidal membership function).

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