Channel Prediction at the Destination for Relay Training Overhead Reduction in Cooperative Wireless Networks

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***Abstract*— Signaling overhead reduction has been a key approach to realizing energy-efficient wireless cooperative communication systems. Motivated by the fact that consecutive temporal samples of real-world wireless channels are typically correlated, this paper proposes to exploit such time-domain correlation for relay training overhead reduction in cooperative networks. Specifically, we consider a cooperative transmit beamforming system, in which relay terminals employing the decode-and-forward protocol collaboratively transmit the source message according to the pre maximal-ratio-combining (pre-MRC) principle. During the training phase, the relays send training signals to aid channel estimation at the destination. Based on the acquired record of the channel state information (CSI), the destination then employs a linear minimum-mean-square-errors (LMMSE) channel predictor to update the CSI; in this way, training overhead dedicated by relays can then be reduced. We derive a closed-form expression for the receive SNR at the destination when the pre-MRC beamforming factors are computed in accordance with the predicted CSI. Our analytic results can be used for characterizing the performance degradation of channel prediction as the duration of the prediction phase is enlarged. The proposed analytic studies are corroborated by numerical simulations.**

I. INTRODUCTION

Cooperative communication is now widely known as a promising technique for realizing distributed spatial diversity in modern wireless networks [1], [2]. To achieve various performance advantages benefiting from user cooperation, knowledge of the system parameters at the relay and destination terminals is typically required. For example, to implement the distributed beamforming/precoding schemes for link reliability enhancement, the relays must know the channel state information (CSI) of the source-to-relay or/and the relay-to-destination communication links [1], [2]. As a result, communication overheads dedicated to information exchange or feedback in a cooperative wireless network are indispensable. To meet the high energy-efficiency demand in next-generation wireless systems, a central issue is thus the reduction, or minimization, of such intra-network communication cost [3]-[5]. In particular, since the wireless relay terminals could be subject to limited infrastructure and energy resource, e.g., small handsets powered by battery, communication overhead reduction for relay nodes is important.

This paper considers a cooperative network, in which the relays employ the decode-and-forward protocol to realize the distributed pre-maximum-ratio-combining (pre-MRC) scheme, as in [6], [7]. To obtain the CSI of the relay-to-destination links, the relays need to periodically send training symbols in each data packet to facilitate CSI estimation/update at the destination. We investigate the problem of training overhead reduction for relay terminals based on channel prediction at the destination. The proposed approach rests on the fact that in the realistic environment the channel gains between consecutive time slots are typically correlated. Hence, once the destination has acquired a record of channel estimates during the past few training phases, it is then plausible to exploit the channel temporal correlation to predict the latest CSI via certain channel prediction schemes. The beamforming weights computed based on the predicted CSI can then be fedback to the relay nodes. In this way, the relays no longer need to frequently send training signals to the destination, and the aggregated communication overheads can be reduced. A schematic description of the proposed approach is shown in Figure 1.

To ease analysis as well as algorithm implementation, the linear minimum mean square error (LMMSE) channel predictor [8] is adopted in this paper. To exploit the spatial diversity, the predicted CSI is fedback to relays so as to realize the distributed pre-maximum-ratio-combining (pre-MRC) scheme, as in [6], [7]. Assuming that the CSI obtained by training-based estimation is exact and the channel mismatch is entirely caused by prediction errors, we derive a closed-form formula for the achievable signal-to-noise ratio (SNR) when the beamforming weights are designed in accordance with the predicted CSI. The proposed analytic results are corroborated by computer simulations. In addition, for a given target SNR threshold, our analytic results allow us to quantify the percentage of reduction in training overheads. The rest of this paper is organized as follows. Section II introduces the system model and problem statement. Section III shows the SNR analysis. Section IV shows the simulation results. Finally, Section V concludes this paper.

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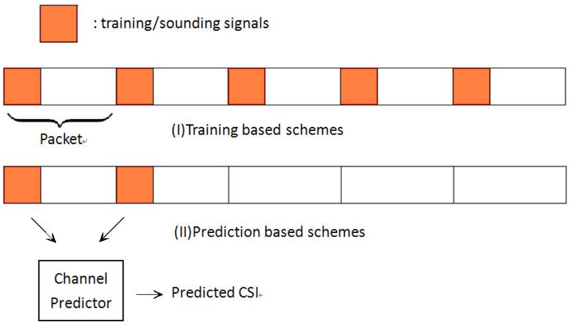

Fig. 1. Frame structures for training based scheme and prediction based scheme.

II. System Models and Problem Statement

We consider a wireless relay network, in which J relay terminals employ the decode-and-forward protocol to cooperatively relay the message sequence $\mathbf{s}[n] \in \mathbb{C}^T$ received from the source at the nth time slot to the destination [1]. We assume that the channel between the jth relay and the destination is flat fading. In addition, each channel is quasi-static and remains constant over one slot. Let $h_j[n] \in \mathbb{C}$, $1 \leq j \leq J$, be the channel gain of the link from the jth relay to the destination at the nth time slot. The following two assumptions about the channel coefficients are made throughout the paper.

Assumption 1: For each fixed n, the channel gains $h_j[n]$'s, $1 \leq j \leq J$, are i.i.d. circularly complex Gaussian random variables with zero mean and unit variance.

Assumption 2: For each fixed j, the temporal variation of the channel follows the Jake's model [9] with the time correlation function given as $E\{h_j[n]h_j^*[m]\} = \sigma_h^2 J_o(2\pi f_d(n-m))$, where $J_0(\cdot)$ is the zero-order Bessel function and f_d is the Doppler frequency in Hertz.

To exploit the distributed spatial diversity, as in [1] and [2], the J relays cooperate to perform the distributed transmit beamforming [6]. Therefore, the received signal at the destination is given as follows:

$$\mathbf{y}[n] = \sum_{j=1}^{J} h_j[n] p_j[n] \mathbf{s}[n] + \mathbf{z}[n], \tag{1}$$

in which the $p_j[n] \in \mathbb{C}$ is the power amplification factor for the jth relay at the nth slot, and $\mathbf{z}[\cdot] \in \mathbb{C}^T$ is the zero-mean complex white Gaussian noise sequence with variance σ_v^2. We assume as in [1] and [7] that $p_j[n]$'s are designed in accordance with the pre-MRC rule, thus

$$p_j[n] = \frac{h_j^*[n]}{\sum_{j=1}^{J} |h_j[n]|^2} \sqrt{SNR_{req}}\sigma_v, \quad 1 \leq j \leq J, \tag{2}$$

where SNR_{req} denotes the target SNR level required for correct symbol decoding at the destination. To realize the pre-MRC advantage, the CSI $h_j[n]$'s must be estimated at the destination and then fedback to each relay. Hence, overheads due to training and information exchange will be inevitable. In this paper, we leverage channel prediction at the destination for relay training overhead reduction, and conduct SNR analysis when the beamforming coefficients are designed based on the predicted CSI.

[1]A time slot spans T symbol intervals.

III. Average SNR Analysis with Channel Prediction

The main purpose of this section is to conduct receive SNR analysis of the pre-MRC scheme (2) implemented on the basis of the predicted CSI. Since the receive SNR attained with the training based scheme will serve as the benchmark, we assume for analytic simplicity that the channels estimated during the training phase are exact and, thus, the channel mismatch is entirely caused by prediction errors. In what follows we denote by $\hat{h}_j[n]$ the acquired CSI about the true $h_j[n]$. If training is performed at the nth slot, we have $\hat{h}_j[n] = h_j[n]$ and, from (1) and (2), the received signal at the destination is

$$\begin{aligned}\mathbf{y}[n] &= \sum_{j=1}^{J} h_j[n] \left[\frac{h_j^*[n]}{\sum_{j=1}^{J} |h_j[n]|^2} \sqrt{SNR_{req}}\sigma_v \right] \mathbf{s}[n] + \mathbf{z}[n] \\ &= \sqrt{SNR_{req}}\sigma_v \mathbf{s}[n] + \mathbf{z}[n]. \end{aligned} \tag{3}$$

That is, the target SNR_{req} is attained by means of training. If the predicted channel gains are employed for the pre-MRC, the transmit power factor (2) becomes

$$p_j[n] = \frac{\hat{h}_j^*[n]}{\sum_{j=1}^{J} |\hat{h}_j[n]|^2} \sqrt{SNR_{req}}\sigma_v, \quad 1 \leq j \leq J, \tag{4}$$

and the received signal (1) then reads

$$\begin{aligned}\mathbf{y}[n] &= \sum_{j=1}^{J} h_j[n] \left[\frac{\hat{h}_j^*[n]}{\sum_{j=1}^{J} |\hat{h}_j[n]|^2} \sqrt{SNR_{req}}\sigma_v \right] \mathbf{s}[n] + \mathbf{z}[n] \\ &= \frac{\sum_{j=1}^{J} h_j[n]\hat{h}_j^*[n]}{\sum_{j=1}^{J} |\hat{h}_j[n]|^2} \cdot \sqrt{SNR_{req}}\sigma_v \mathbf{s}[n] + \mathbf{z}[n]. \end{aligned} \tag{5}$$

From (5), the achievable average SNR with channel prediction is

$$\overline{SNR}_{pre}[n] = \beta[n] SNR_{req}, \tag{6}$$

with

$$\beta[n] \triangleq \frac{E\left\{\left|\sum_{j=1}^{J} h_j[n]\hat{h}_j^*[n]\right|^2\right\}}{E\left\{\left|\sum_{j=1}^{J} |\hat{h}_j[n]|^2\right|^2\right\}}, \quad (7)$$

in which the expectation is taken with respect to the spatial channel statistics. The rest of this section aims at characterizing the effect of channel prediction on the $\overline{SNR}_{pre}[n]$. We assume that the predicted channels at the destination are obtained based on the LMMSE criterion; an overview of the LMMSE predictor is given in Section III-A. In Section III-B, we derive a closed-form formula for $\overline{SNR}_{pre}[n]$. With the analytical results, the advantages of training overhead reduction will be studied in the next section.

A. LMMSE Channel Prediction

Assume that training based channel estimation is performed at the time slots $n = 1, 2, \cdots, K$, thus $\hat{h}_j[n] = h_j[n]$ for all $1 \le n \le K$ and $1 \le j \le J$. To obtain the channel information for the $(K+1)$th slot, the destination implements a bank of J linear predictors, each of order K, as

$$\begin{aligned}\hat{h}_j[K+1] &= \sum_{k=1}^{K} c_{j,k}^* \hat{h}_j[K+1-k] \\ &= \sum_{k=1}^{K} c_{j,k}^* h_j[K+1-k], \quad 1 \le j \le J. \quad (8)\end{aligned}$$

For each $1 \le j \le J$, the associated predictor coefficients $c_{j,k}$'s designed according to the well-known LMMSE criterion can be obtained by solving the linear equation [8]

$$\sum_{l=1}^{K} c_{j,l} R_j[k-l] = R_j[k], \quad 1 \le k \le K, \quad (9)$$

where the channel auto-correlation function is given by $R_j[k] = E\{h_j[m]h_j^*[m-k]\} = \sigma_h^2 J_0(2\pi f_d k)$ (cf. Assumption 2). Once $\hat{h}_j[K+1]$ is available, one can obtain $\hat{h}_j[K+2]$ as a linear combination of the K most recent channel samples $\hat{h}_j[K+1], h_j[K], \cdots, h_j[2]$ characterized by the recursive equation (8), and likewise for $\hat{h}_j[K+i]$ with $i > 1$. To facilitate average SNR analysis in the next subsection, we first derive the general expression for the predicted channel gains $\hat{h}_j[K+i]$, $i > 1$, in terms of $h_j[1], \cdots, h_j[K]$. This is given in the next lemma (the proof is omitted due to space limitation).

Lemma 1: For $n \ge K+1$, we have

$$\hat{h}_j[n] = \sum_{k=1}^{K} w_{j,k}[n-K] h_j[K+1-k], \quad (10)$$

where

$$w_{j,k}[n] = c_{j,k}^* \cdot w_{j,1}[n-1] + w_{j,k+1}[n-1], \quad (11)$$

with $w_{j,1}[0] = 1$, $w_{j,2}[0] = w_{j,3}[0] = \cdots = w_{j,K}[0] = 0$, and $w_{j,K+1}[n-1] = 0$.

□

B. Average SNR Analysis

With the aid of Lemma 1, we derive a closed-form formula for $\overline{SNR}_{pre}[n]$ in the channel prediction phase. To proceed, we shall first leverage Lemma 1 to rewrite $\beta[n]$ in (7) in a more compact and tractable form. For this let us stack all the spatial and temporal channel coefficients into a vector as

$$\begin{aligned}\mathbf{h} \;=\; & [h_1[n], \cdots, h_1[1], h_2[n], \cdots, ,h_2[1], \\ & \cdots, h_J[n], \cdots, h_J[1]]^T \in \mathbb{C}^{Jn}. \quad (12)\end{aligned}$$

Based on Lemma 1, we have the following result (the proof is omitted due to space limitation).

Lemma 2: Let $\beta[n]$ be defined in (7). Then we have

$$\beta[n] = \frac{E\{|\mathbf{h}^H \mathbf{W}_1 \mathbf{h}|^2\}}{E\{|\mathbf{h}^H \mathbf{W}_2 \mathbf{h}|^2\}}, \quad (13)$$

in which (i) $\mathbf{W}_1 \in \mathbb{C}^{Jn \times Jn}$ is $(n \times n)$-block diagonal with the jth diagonal block given by

$$\mathbf{W}_{1,j} = \begin{bmatrix} \mathbf{0}_{(n-K)\times 1} & \mathbf{0}_{(n-K)\times(n-1)} \\ \mathbf{r}_{1,j} & \mathbf{0}_{K\times(n-1)} \end{bmatrix} \in \mathbb{C}^{n\times n} \quad (14)$$

and

$$\begin{aligned}\mathbf{r}_{1,j} \;=\; & \big[w_{j,1}^*[n-K] \;\; w_{j,2}^*[n-K] \;\; \cdots \\ & w_{j,K}^*[n-K]\big]^T \in \mathbb{C}^K; \quad (15)\end{aligned}$$

(ii) $\mathbf{W}_2 \in \mathbb{C}^{Jn \times Jn}$ is $(n \times n)$-block diagonal with the jth diagonal block given by

$$\mathbf{W}_{2,j} = \begin{bmatrix} \mathbf{0}_{(n-K)\times(n-K)} & \mathbf{0}_{(n-K)\times K} \\ \mathbf{0}_{K\times(n-K)} & \mathbf{r}_{2,j} \end{bmatrix} \in \mathbb{C}^{n\times n} \quad (16)$$

and

$$\mathbf{r}_{2,j} = \begin{bmatrix} |w_{j,1}[n-K]|^2 & \cdots & w_{j,1}^*[n-K]\cdot w_{j,K}[n-K] \\ w_{j,1}[n-K]\cdot w_{j,2}^*[n-K] & \cdots & w_{j,2}^*[n-K]\cdot w_{j,K}[n-K] \\ \vdots & \ddots & \vdots \\ w_{j,1}[n-K]\cdot w_{j,K}^*[n-K] & \cdots & |w_{j,K}[n-K]|^2 \end{bmatrix} \in \mathbb{C}^{K\times K}. \quad (17)$$

□

Based on (13), the average SNR reads

$$\beta[n]SNR_{req} = \frac{E\left\{|\mathbf{h}^H \mathbf{W}_1 \mathbf{h}|^2\right\}}{E\left\{|\mathbf{h}^H \mathbf{W}_2 \mathbf{h}|^2\right\}} SNR_{req}. \tag{18}$$

Toward an analytic expression of the average SNR, it remains to find a closed-form formula of $\frac{E\left\{|\mathbf{h}^H \mathbf{W}_1 \mathbf{h}|^2\right\}}{E\left\{|\mathbf{h}^H \mathbf{W}_2 \mathbf{h}|^2\right\}}$, which involves the ratio of the expected value of the squared quadratic form in the random vector $\mathbf{h}$. Based on (10) and with the aid of [10], we reach the following main result (the proof is omitted due to space limitation).

Theorem 1: Let $\mathbf{W}_1 \in \mathbb{C}^{Jn \times Jn}$ and $\mathbf{W}_2 \in \mathbb{C}^{Jn \times Jn}$ be defined as in Lemma 2. A closed-form expression of $\overline{SNR}_{pre}[n]$ can be obtained by

$$\overline{SNR}_{pre}[n] = \frac{(Tr[\mathbf{W}_3\mathbf{H}])^2 + Tr[(\mathbf{W}_3\mathbf{H})^2]}{(Tr[\mathbf{W}_2\mathbf{H}])^2 + Tr[(\mathbf{W}_2\mathbf{H})^2]} \cdot SNR_{req}, \tag{19}$$

where $\mathbf{W}_3 = (\mathbf{W}_1 + \mathbf{W}_1^H)/2$, and $\mathbf{H} = E\{\mathbf{h}\mathbf{h}^H\} \in \mathbb{C}^{Jn \times Jn}$ is $(n \times n)$-block diagonal with jth diagonal block given by

$$\mathbf{H}_j = \begin{bmatrix} R_j[0] & R_j[1] & \cdots & R_j[n-1] \\ R_j[1] & R_j[0] & \cdots & R_j[n-2] \\ \vdots & \vdots & \ddots & \vdots \\ R_j[n-1] & R_j[n-2] & \cdots & R_j[0] \end{bmatrix} \in \mathbb{C}^{n \times n}; \tag{20}$$

$$Tr[\mathbf{W}_2\mathbf{H}] = \sum_{j=1}^{J} \sum_{k'=1}^{K} \sum_{k=1}^{K} w_{j,k'}^*[n-K] \cdot w_{j,k}[n-K] R_j[k-k']; \tag{21}$$

$$Tr[(\mathbf{W}_2\mathbf{H})^2] = \sum_{j=1}^{J} \left(\sum_{k'=1}^{K} \sum_{k=1}^{K} w_{j,k'}^*[n-K] \right. \\ \left. \cdot w_{j,k}[n-K] R_j[k-k'] \right)^2; \tag{22}$$

$$Tr[\mathbf{W}_3\mathbf{H}] = \sum_{j=1}^{J} \sum_{k=1}^{K} Re\{w_{j,k}[n-K]\} \cdot R_j[n+k-K-1]; \tag{23}$$

$$Tr[(\mathbf{W}_3\mathbf{H})^2] = \frac{1}{4} \sum_{j=1}^{J} \left[2R_j[0] \cdot \sum_{k'=1}^{K} \sum_{k=1}^{K} w_{j,k'}^*[n-K] \right. \\ \cdot w_{j,k}[n-K] \cdot R_j[k-k'] \\ + \left(\sum_{k=1}^{K} w_{j,k}[n-K] \cdot R_j[n+k-K-1] \right)^2 \\ \left. + \left(\sum_{k=1}^{K} w_{j,k}^*[n-K] \cdot R_j[n+k-K-1] \right)^2 \right]. \tag{24}$$

□

The result of Theorem 1 allows us to determine the duration of the channel prediction phase, hereafter denoted by T_p ($1 \le T_p < \infty$), that can sustain a given target SNR threshold. Specifically, from (19), T_p can be found according to

$$T_p(\gamma) = \arg\max_n \left\{ \frac{\overline{SNR}_{pre}[n]}{SNR_{req}} = \beta[n] \le \gamma \right\}; \tag{25}$$

in (25), $0 < \gamma \le 1$ is the threshold specifying a tolerable SNR level. The function $\beta[n]$, however, is highly nonlinear in n. Hence, a closed-form solution of $T_p(\gamma)$ is difficult to obtain. Despite this, one can still resort to computer simulation to find a solution, as shown in the next section. Once T_p is determined according to (25), the percentage of reduction in the training overhead is thus

$$\eta = \left(\frac{T_p(\gamma)}{T_t + T_p(\gamma)}\right) \times 100\%. \tag{26}$$

IV. Simulation Results

This section conducts several numerical simulations to evidence our analytic study. We consider a cooperative network with five relay terminals, thus $J = 5$. For simplicity, the moving velocity of all relays is assumed to be identical, hereafter denoted by v. During the training phase, pilot signals are inserted in consecutive T_t time slots for channel estimation; afterwards channel prediction based on the acquired T_t channel coefficients are conducted in order to predict the CSI for the next T_p slots; the order of the channel predictors at the destination are thus set to be $K = T_t$. To quantify the efficacy of the proposed prediction based approach, we consider the ratio $\beta[n_p] = \overline{SNR}_{pre}[n_p]/SNR_{req}$, for $1 \le n_p \le T_p$ (thus $0 < \beta[n_p] \le 1$); a large value of $\beta[n_p]$ thus corresponds to better channel prediction accuracy, and is expected to yield small SNR degradation.

For carrier frequency f_c = 1 G Hz and velocity v = 10 km/hr, Figure 2 plots $\beta[n_p]$ for different predictor order $K(= T_t)$. It can be seen from the figure that the derived analytic result closely matches the simulated outcome. Also, as K increases, channel prediction is more accurate, and the decay of $\beta[n_p]$ as n_p increases is less rapid. With fixed K = 3, Figure 3 depicts $\beta[n_p]$ at different f_c (with v = 10 km/hr), whereas Figure 4 shows $\beta[n_p]$ for different velocity v (with f_c = 1 G Hz). From both figures, it can be seen that degradation of channel prediction performance is small provided that f_c is small or the mobility is low; this is expected since, in either case, the channel temporal variation is less severe, and the correlation between consecutive channel measurements is large. In particular, for v = 5 km/hr, more than ninety percent of SNR_{req} is sustained even though n_p is as large as 100; this means that, after the training phase, good CSI quality can be acquired during the next 100 slots via channel prediction (thus frequent training is no longer needed). To further illustrate the achievable reduction in the training overhead, we set the threshold $\gamma = 0.9$ and determine the resultant $T_p(0.9)$ (cf. (25)) for different velocities by using the results of Figure 4. The achievable percentage of reduction η computed using (26) is listed in Table I. The result shows that conservation of the training overhead is significant when mobility is low.

V. Conclusions

Signaling overhead reduction is a key means of realizing energy-efficient wireless communications for the forth-

TABLE I

TRAINING OVERHEAD REDUCTION η IN (26) ($\gamma = 0.9$ AT $K = 3$ AND $f_c = 1$ GHZ).

v (km/hr)	5	10	15	25	60
η (%)	96.6	93.2	90.0	84.2	66.7

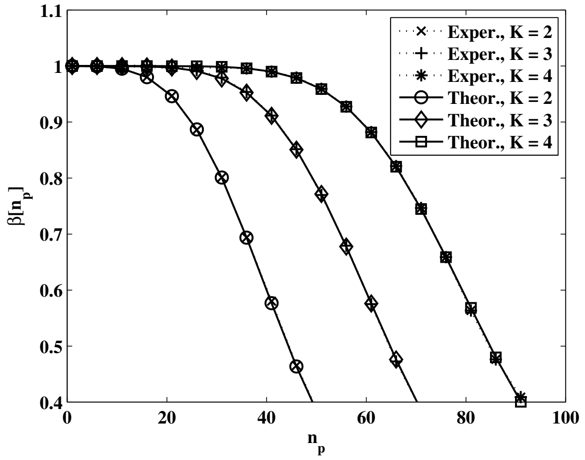

Fig. 2. The variation of $\beta[n_p]$ for varying prediction orders at f_c = 1 GHz and v = 10 km/hr.

generation and beyond. By exploiting the temporal correlation of wireless channels, this paper proposes a low-overhead CSI acquisition scheme for cooperative beamforming systems. To reduce the training overhead of relays, linear channel prediction is employed at the destination to update the CSI based on the channel estimates obtained during the training phase. The main contribution of this paper is the receive SNR performance analysis when the beamforming weights are designed in accordance with the predicted CSI. Specifically, under the assumption that the CSI obtained by training-based estimation is exact and the channel mismatch is entirely caused by prediction errors, we derive a closed-form formula of the receive SNR. Our analytic study is evidenced by computer simulations; in addition, it allows us to quantify the amount of training overhead reduction. On-going studies will focus on SNR analysis that further takes channel estimation error into consideration. Moreover, new criteria for determining the duration of the channel prediction phase that are based on cross-layer design metrics, e.g., joint SNR and system throughout, is currently under investigation.

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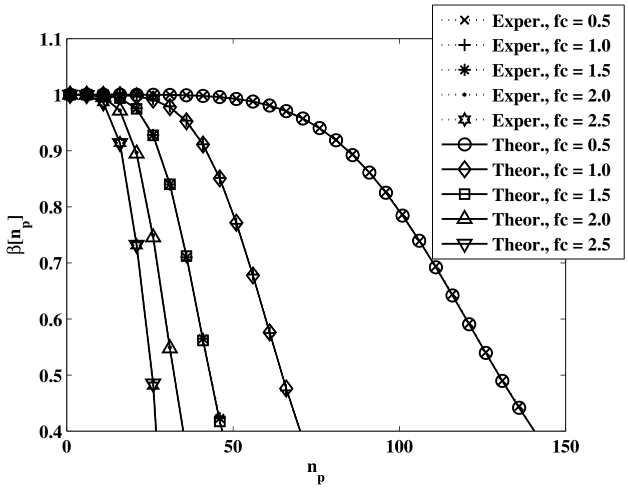

Fig. 3. The variation of $\beta[n_p]$ for varying carrier frequencies at $K = 3$ and $v = 10$ km/hr.

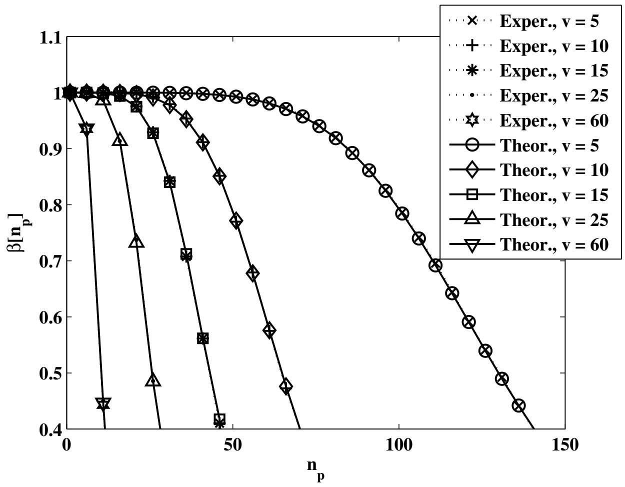

Fig. 4. The variation of $\beta[n_p]$ for varying relay mobilities at $K = 3$ and f_c = 1 GHz.

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