2005 American Control Conference
June 8-10, 2005. Portland, OR, USA



# Stochastic Power Control for Time-Varying Lognormal Fading Wireless Channels

Mohammed M. Olama, Shoaib M. Shajaat, Seddik M. Djouadi, and Charalambos D. Charalambous

*Abstract*—**The performance of stochastic optimal power control of time varying lognormal fading channels, in which the evolution of the dynamical channel is described by stochastic differential equations (SDE's), is determined. Unlike the common random static models, the SDE's essentially capture the spatial-temporal variations of wireless channels. The solution of the stochastic optimal power control is obtained through path-wise optimization, which is solved by linear programming using a predictable power control strategy. The algorithm can be implemented using an iterative numerical scheme. The performance measure is interference or outage probability. Numerical results indicate that the performance of this algorithm is close to the optimal case as long as the channel model does not change significantly.**

## I. INTRODUCTION

TRANSMITTER power is an important resource in cellular mobile radio communication systems [1]. The control of the transmitted power provides for an efficient and optimal performance of wireless communication systems. It can increase system capacity and quality of communications [2]. Co-channel interference caused by frequency reuse is the most restraining factor on the system capacity. The measure of quality usually employed in cellular systems design is the signal to interference ratio (SIR) [2]. The SIR defines the strength and quality of the received signal. Users only need to expend sufficient power for acceptable reception as determined by their quality of service (QoS) specifications.

The power allocation problem has been studied extensively as an eigenvalue problem for non-negative matrices [1-5], as iterative power control (PC) algorithms that converge each user power to the minimum power result [6-9], and as optimization based approaches [10, 11]. An optimal control algorithm for distributed power control (DPC) in cellular communication systems was proposed by [12]. A cost is defined for each mobile that consists of a weighted sum of power, power update, and SIR error. Much of this work deals with time invariant channel models. In this paper, centralized power control (CPC) and closed loop PC schemes are used.

Any PC scheme that attempts to follow fast fades would need to be highly efficient to be implemented in practice, or incur a power penalty due to intense signal processing and may require frequent communication with its assigned base station. Of particular interest is the work presented in [10, 11]. In [10], a scheme whereby the statistics of the received SIR are used to allocate power, rather than an instantaneous SIR. The allocation decisions can then be made on a much slower time scale (following lognormal shadowing variations for instance).

The majority of research has been done in this field uses static models for the wireless channels. In static (time-invariant) models, all the channel parameters are random but remain constant throughout the observation and estimation phase. In dynamical (time-varying) models, the channel characteristics change with respect to both space and time [13, 14, 15]. In this paper the time-varying lognormal wireless channel model is described by stochastic differential equation (SDE), and a power control algorithm (PCA) called predictable power control strategy (PPCS) is applied [16]. The correct usage of any PCA and thereby the power optimization of the channel models, require the use of such channel models that capture both temporal and spatial variations in the channel. These models exhibit more realistic behavior of wireless communication systems [17]. Since very few spatial-temporal dynamical models have so far been investigated with the application of any PCA, the suggested dynamical model and the PCA will thus provide a far more realistic and efficient optimal control for wireless fading channels.

The PPCS algorithm first proposed in [16] is used to minimize the total transmitted power for more realistic dynamical lognormal channel model. The PPCS takes into account the presence of noise in the channel and makes use of time varying dynamical link for an efficient PC of transmitters. Also the iterative PCA presented in [7, 9] can be used to determine the optimal powers iteratively. This helps in allowing autonomous execution at the node or link level, requiring minimal usage of network communication resources for control signaling.

Simulation results are provided comparing the performance of the proposed method (i.e. PPCS) with the performance of no power control (NPC).

Mohammed M. Olama, Department of Electrical and Computer Engineering, University of Tennessee, 1508 Middle Dr., Knoxville, TN 37996, USA (E-mail: molama@utk.edu).
Shoaib M. Shajaat, Department of Applied Science, University of Arkansas at Little Rock, 2801 South University Ave., Little Rock, AR 72204, USA (E-mail: smshajaat@ualr.edu).
Seddik M. Djouadi, Department of Electrical and Computer Engineering, University of Tennessee, 1508 Middle Dr., Knoxville, TN 37996, USA (E-mail: djouadi@ece.utk.edu).
Charalambos D. Charalambous, Department of Electrical and Computer Engineering, University of Cyprus, 75, Kallipoleos Street, P.O.Box 20537, 1678 Nicosia, Cyprus (E-mail: chadcha@ucy.ac.cy).

## II. TIME VARYING LOGNORMAL FADING CHANNEL MODEL

In the real world, signals travel between mobiles and base stations are affected by a number of factors that are characterized by time-variation and time spreading [18]. Therefore there exist many factors that define the uncertainties (randomness) and the changing conditions with respect to time and/or space (stochastic) within the wireless communication channel. The static models do not take into account the time varying behavior of the channel and its statistics, therefore they do not represent a realistic picture of the communication medium. For this very important reason, it becomes essential to make use of stochastic dynamical channel models to investigate the true behavior of the wireless communication network and analyze the correct effectiveness of PC.

In the static case, the power loss (PL) in dB for a given path is given by [19]:

$$PL(d)[dB] := \overline{PL}(d_0)[dB] + 10\alpha \log\left(\frac{d}{d_0}\right) + \tilde{X}, \ \ d \ge d_0 \quad (1)$$

where $\overline{PL}(d_0)$ is average PL in dB at a reference distance $d_0$ from the transmitter, $\alpha$ is the path-loss exponent which depends on the propagation medium, and $\tilde{X}$ is a zero-mean Gaussian distributed random variable, which represents the variability of PL due to numerous reflections occurring along the path and possibly any other uncertainty of the propagation environment from one observation instant to the next.

In Dynamical model, the average PL becomes a random process denoted by $\{X(t,\tau)\}_{t\ge 0, \tau \ge \tau_0}$, which is a function of both time $t$ and location represented by $\tau$, where $\tau = d/c$, $d$ is the path length, $c$ is the speed of light, $\tau_o = d_o/c$ and $d_o$ is the reference distance. $\{X(t,\tau)\}_{t\ge 0, \tau \ge \tau_0}$ represents how much power the signal loses at a particular distance as a function of time [13]. The signal attenuation is defined by $S(t,\tau) = e^{kX(t,\tau)}$, where $k = -c/2$ and $c = \ln(10)/10$ [14]. $X(t,\tau)$ is generated by a mean-reverting version of a general linear SDE given by [15]:

$$\begin{aligned} &dX(t,\tau) = \beta(t,\tau)\big((\gamma(t,\tau) - X(t,\tau)\big)dt + \delta(t,\tau)dW(t), \\ &X(t_0,\tau) = N(\overline{PL}(d)[dB]; \sigma_{t_0}^2) \end{aligned} \quad (2)$$

where $\{W(t)\}_{t\ge 0}$ is the standard Brownian motion (zero drift, unit variance) which is assumed to be independent of $X(t,\tau)$, and $N(\mu;\kappa)$ denotes a Gaussian random variable with mean $\mu$ and variance $\kappa$, and $\overline{PL}(d)$[dB] is the average PL in dB. The parameter $\gamma(t,\tau)$ models the average time-varying PL at distance $d$ from transmitter, which corresponds to $\overline{PL}(d)$[dB] at $d$ indexed by $t$. This model tracks and converges to this value as time progresses. The instantaneous drift $\beta(t,\tau)\big(\gamma(t,\tau) - X(t,\tau)\big)$ represents the effect of pulling the process towards $\gamma(t,\tau)$, while $\beta(t,\tau)$ represents speed of adjustment towards this value. Finally, $\delta(t,\tau)$ controls the instantaneous variance or volatility of the process for the instantaneous drift. The initial condition of $X(t,\tau)$ can be obtained from geometric Brownian motion model which calculates $X(t_0,\tau)$ for a fixed $t = t_0$ as a function of $\tau$ [15, 17].

Let $\{\theta(t,\tau)\}_{t\ge 0} = \{\beta(t,\tau), \gamma(t,\tau), \delta(t,\tau)\}_{t\ge 0}$. If the random processes $\{\theta(t,\tau)\}_{t\ge 0}$ are measurable and bounded, (2) has a unique solution for every $X(t_0,\tau)$ given by:

$$X(t,\tau) = e^{-\beta([t,t_0],\tau)} \left( \begin{aligned} &X(t_0,\tau) + \int_{t_0}^{t} e^{\beta([u,t_0],\tau)} [\beta(u,\tau)\gamma(u,\tau)du \\ &+\delta(u,\tau)dW(u)] \end{aligned} \right) \quad (3)$$

where $\beta([t,t_0],\tau) \triangleq \int_{t_0}^{t} \beta(u,\tau)du$.

This model captures the temporal and spatial variations of the propagation environment as the random parameters $\{\theta(t,\tau)\}_{t\ge 0}$ can be used to model the time and space varying characteristics of the channel. It is required that the mean of PL process $E[X(t,\tau)]$ should track time and space variations of the average PL. For example, let

$$\gamma(t,\tau) = \gamma_m \left(1 + 0.15 e^{-2t/T} \sin\left(\frac{10\pi t}{T}\right)\right) \quad (4)$$

where $\gamma_m$ is the average PL and $T$ is the observation interval. The variations of $X(t,\tau)$ as a function of distance and time are represented in Fig. 1, where $\delta(t) = 1400$ and $\beta(t) = 225000$ (these parameters are determined from experimental measurements).

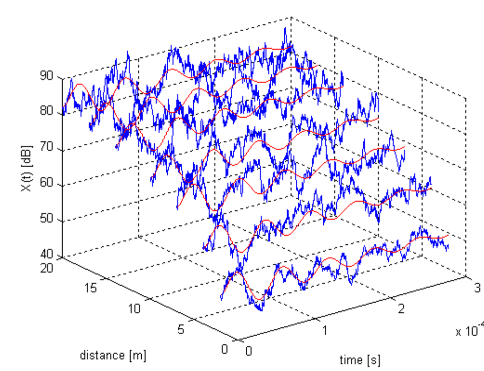



Fig. 1: Mean-reverting power PL as a function of $t$ and $\tau$, for a given time varying $\gamma(t,\tau)$.

In Fig. 1, the temporal variations of the environment are captured by a time varying $\gamma(t,\tau)$ which was chosen such as to fluctuate around different average PL's ($\gamma_m$'s), thus each curve corresponds to a different location.

In spatial-temporal lognormal model, besides initial distances, the motion of mobiles, i.e., their velocities and directions of motion with respect to their base stations are important factors to evaluate time varying power path losses for the links involved. This can be illustrated in a simple way for the case of one transmitter and one receiver. Consider a receiver at a distance $d$ from a transmitter and moves with a certain constant velocity $\upsilon_m$ in a direction defined by an arbitrary constant angle $\theta_n$, where $\theta_n$ is the angle between the direction of motion of the mobile and the distance vector that starts from the transmitter towards the receiver as shown in Fig. 2:

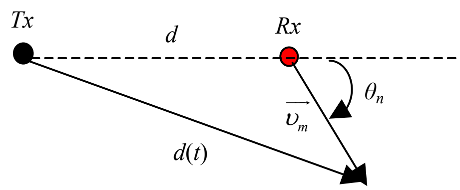



Fig. 2: A receiver (mobile) at a distance $d$ from a transmitter (base station) moves with velocity $\upsilon_m$ and in direction given by $\theta_n$ with respect to the transmitter-receiver axis.

At time $t$, the new distance from the transmitter to the receiver $d(t)$ is given by:

$$d(t) = \sqrt{d^2 + (\upsilon_m t)^2 + 2.d.t.\upsilon_m.\cos\theta_n} \tag{5}$$

Therefore, the average PL at that new location is given by:

$$\gamma(t,\tau) = \overline{PL}(d_0)[dB] + 10\alpha \log\frac{d(t)}{d_0} + \xi(t) \tag{6}$$

where $d(t) \geq d_0$ and $\overline{PL}(d_0)$ is average PL in dB at a reference distance $d_0$, $d(t)$ is defined in (5), $\alpha$ is the PL coefficient and $\xi(t)$ is an arbitrary function of time representing the temporal variations in the propagation environment like the appearance and disappearance of additional scatters.

The next section describes a PCA that uses the previous time-varying channel model to achieve the minimal transmitted power in stochastic lognormal fading channels.

## III. POWER CONTROL MODEL

### A. Stochastic Power Control Scheme

Consider a wireless network of $M$ transmitters and $M$ receivers. The measure of quality of service (QoS) in deterministic case can be defined through SIR as [16]:

$$\min_{(p_1 \geq 0,\dots,p_M \geq 0)} \sum_{i=1}^{M} p_i \tag{7}$$

subject to

$$\frac{p_n g_{nn}}{\sum_{j\neq n}^{M} p_j g_{nj} + \eta_n} \geq \overline{\gamma}_n \tag{8}$$

Equation (8) is equivalent to

$$\frac{p_n g_{nn}}{\sum_{j=1}^{M} p_j g_{nj} + \eta_n} \geq \gamma_n \tag{9}$$

where $\gamma_n := \dfrac{\overline{\gamma}_n}{\overline{\gamma}_n + 1}$, $0 < \gamma_n < 1$. Here $p_n$ denotes the power of transmitter $n$, $g_{nj} > 0$ denotes the channel gain of transmitter $j$ to the receiver assigned to transmitter $n$, $\overline{\gamma}_n > 0$ is the required SIR and $\eta_n > 0$ is the noise power level at the $n$th receiver, $1 \leq n, j \leq M$.

Using the path-wise QoS of each user with respect to the power signals over a time interval $[0,T]$, the system (7) and (9) in dynamic case is given as:

$$\min_{(p_1 \geq 0,\dots,p_M \geq 0)} \left\{ \sum_{i=1}^{M} \int_0^T p_i(t) \right\}, \text{ subject to}$$

$$\frac{\int_0^T p_n(t) \|S_{nn}(t)\|^2 \, dt}{\sum_{j=1}^{M} \int_0^T p_j(t) \|S_{nj}(t)\|^2 \, dt + \int_0^T \|d_n(t)\|^2 \, dt} \geq \gamma_n \tag{10}$$

where $S_{nj}(t)$ is the signal attenuation coefficients from transmitter $j$ to receiver assigned to transmitter $n$ at time $t$, $d_n(t)$ is the channel disturbance at the $n$th receiver at time $t$, $\|.\|$ is the Euclidean norm, and $1 \leq n \leq M$. The signal attenuation coefficients $S_{nj}(t)$ in (10) are generated using the SDE in (2) and the relation $S(t,\tau) = e^{kX(t,\tau)}$, where $k = -c/2$ and $c = \ln(10)/10$ [14].

PPCS is used to find the solution to (10). In wireless cellular networks, it is practical to observe and estimate channels at base stations and then communicate the information to the transmitters to adjust their control input signals $\{u_k(t)\}_{k=1}^{M}$. Since channel experiences delays, and the control are not feasible continuously in time but only at discrete time instants, the concept of predictable strategies is introduced [16]. Let the channel information at any time $t$ be denoted by $\{S(t)\}$, and let the control input signal for a transmitter at discrete time be $\{u(t);\, t = t_1, t_2, \cdots, T\}$. At time $t_{j-1}$, the base station observes the channel information $\{S_k(t_{j-1})\}_{k=1}^{M}$. Using the concept of predictable strategy, the base station determines the control strategy $\{u_k(t_j)\}_{k=1}^{M}$ for the next time instant $t_j$. The latter is communicated back to the transmitters which hold these values during the time interval $\left[t_{j-1}, t_j\right)$. At time $t_j$, a new set of channel information $\left\{S_k(t_j)\right\}_{k=1}^{M}$ is observed at the base station and the time $t_{j+1}$ control strategies $\left\{u_k(t_{j+1})\right\}_{k=1}^{M}$ are computed and then communicated to the transmitters and held constant during the time interval $\left[t_j, t_{j+1}\right)$. Such decision strategies are called predictable strategies. Using the concept of PPCS over any time interval defined as [$t_k$, $t_{k+1}$], the equivalence of (10) is [16]:

$$\min_{p_i(t_{k+1})} \sum_{i=1}^{M} p_i(t_{k+1}), \text{ subject to}$$
$$P(t_{k+1}) \geq \Gamma G_I^{-1}(t_k, t_{k+1}) \times (G(t_k, t_{k+1}) P(t_{k+1}) + \eta(t_{k+1})) \tag{11}$$

where,

$g_{ni}(t_k, t_{k+1}) := \int_{t_k}^{t_{k+1}} \left\|S_{ni}(t)\right\|^2 dt,\ 1 \leq n, i, \leq M,$

$\eta_{ni}(t_k, t_{k+1}) := \int_{t_k}^{t_{k+1}} \left\|d_n(t)\right\|^2 dt,\ 1 \leq n, i, \leq M,$

$G_I(t_k, t_{k+1}) = diag\left(g_{11}(t_k, t_{k+1}), \cdots, g_{MM}(t_k, t_{k+1})\right),$

$G(t_k, t_{k+1}) = \left\{(g_{ni}(t_k, t_{k+1})\right\}_{M \times M},\ 1 \leq n, i, \leq M,$

$\eta(t_k, t_{k+1}) = (\eta_1(t_k, t_{k+1}), \cdots, \eta_M(t_k, t_{k+1}))^T,$

$P(t_{k+1}) = (p_1(t_{k+1}), \cdots, p_M(t_{k+1}))^T,$

$\Gamma = diag(\gamma_1, \cdots, \gamma_M)$, *diag* (.) denotes a diagonal matrix, and '*T*' stands for matrix or vector transpose. The optimization in (11) is a linear programming problem in $M \times 1$ vector of unknown's $p$ ($t_{k+1}$). Here [$t_k$, $t_{k+1}$] denotes time interval of the signal such that the channel model does not change significantly.

The performance measure is interference or outage probability. It is defined as the probability that a randomly chosen link will fail due to excessive interference [2]. Therefore, smaller outage probability implies larger capacity of the wireless network. A link with received SIR $\overline{\gamma}_{rcvd}$ less than or equal to SIR threshold $\overline{\gamma}_{th}$ is considered a communication failure. The outage probability $F\left(\overline{\gamma}_{rcvd}\right)$ is expressed as $F(\overline{\gamma}_{th}) = \Pr\{\overline{\gamma}_{rcvd} \leq \overline{\gamma}_{th}\}$, where $F\left(\overline{\gamma}_{rcvd}\right)$ is the distribution of $\overline{\gamma}_{rcvd}$.

### B. *Iterative Power Control Scheme*

Since PC only occurs at discrete time instants using PPCS, the iterative algorithm described in [7, 9] can be used to determine the optimal transmitted powers. Define $F(t_k, t_{k+1}) \triangleq \Gamma * G_I^{-1}(t_k, t_{k+1}) * G(t_k, t_{k+1})$ and $u(t_k, t_{k+1}) = \Gamma * G_I^{-1}(t_k, t_{k+1}) * \eta(t_{k+1})$, where

$$u(t_k, t_{k+1}) = \left(\frac{\gamma_1 \eta_1(t_{k+1})}{G_{11}(t_k, t_{k+1})}, \frac{\gamma_2 \eta_2(t_{k+1})}{G_{22}(t_k, t_{k+1})}, \ldots, \frac{\gamma_M \eta_M(t_{k+1})}{G_{MM}(t_k, t_{k+1})}\right)$$

and $Fij(t_k, t_{k+1}) = \dfrac{\gamma_i G_{ij}(t_k, t_{k+1})}{G_{ii}(t_k, t_{k+1})}$, $1 \leq i, j \leq M$. Then the constraint in (11) can be rewritten as:

$$(I - F(t_k, t_{k+1})) P(t_{k+1}) \geq u(t_k, t_{k+1}) \tag{12}$$

The matrix $F(t_k, t_{k+1})$ has nonnegative elements and is irreducible. The existence of a feasible power vector $P(t_{k+1}) > 0$ satisfying (12) is equivalent to $\rho_{F(t_k, t_{k+1})} < 1$, where $\rho_{F(t_k, t_{k+1})}$ is the maximum modulus eigenvalue of $F(t_k, t_{k+1})$. The power vector $P^*(t_{k+1}) = (I - F(t_k, t_{k+1}))^{-1} u(t_k, t_{k+1})$ is the optimal power vector satisfying (11), and the iteration

$$P^{n+1}(t_{k+1}) = F(t_k, t_{k+1}) P^n(t_{k+1}) + u(t_k, t_{k+1}) \tag{13}$$

converges to $P^*(t_{k+1})$ when $\rho_{F(t_k, t_{k+1})} < 1$, where $n$ is the number of iterations. Equation (13) can be written as:

$$P_i^{n+1}(t_{k+1}) = \left(\frac{\gamma_i}{G_{ii}(t_k, t_{k+1})}\right)\left(\sum_{j=1}^{M} G_{ij}(t_k, t_{k+1}) P_j^n(t_{k+1}) + \eta_i(t_k, t_{k+1})\right) \tag{14}$$

and also can be written as:

$$P_i^{n+1}(t_{k+1}) = \frac{\overline{\gamma}_i}{\overline{\gamma}_{rcvd}^{n}(t_k, t_{k+1})} P_i^n(t_{k+1}) \tag{15}$$

where $i = 1, \ldots, M$, and $n$ is the number of iterations. It is shown in [7, 9] that the iterative power control in (14) and (15) converges to the optimal (minimal) power vector.

## IV. NUMERICAL RESULTS

In this section, we give two numerical examples to determine the outage probability for the proposed PCA. In the first example the performance of PPCS is compared with the performance of NPC. In the second example the performance of PPCS is determined for two different velocities. In this model, it is assumed that only mobiles (transmitters) are movable while base stations (receivers) are fixed at one place throughout the time of simulation.

The cellular model has the following features:

- Number of transmitters and receivers is $M = 24$.
- Initial distances of all mobiles with respect to their own base stations $d_{ii}$ are generated as uniformly independent identically distributed (*i.i.d.*) random variables (*r.v.*'s) in [10 – 100] meters.
- Cross initial distances of all mobiles with respect to other base stations $d_{ij}, i \neq j$, are generated as uniformly *i.i.d. r.v.*'s in [250 - 550] meters.
- The angle $\theta_{ij}$ between the direction of motion of mobile $j$ and the distance vector passes through base station $i$ and the mobile $j$ are generated as uniformly *i.i.d. r.v.*'s in [0 – 180] degrees.
- The average velocities of mobiles are generated as uniformly *i.i.d. r.v.*'s in [40 – 100] km/hr.

- All mobiles move at sinusoidal variable speeds around the average speeds during the simulation period.
- PL exponent is 3.5.
- Initial reference distance from each of the transmitters is 10 m.
- PL at the initial reference distance is 67 dB.
- $\delta(t) = 1400$ and $\beta(t) = 225000$ for the SDE's.
- $\eta_n$'s are independent random variables with zero mean and variance = $4*10^{-8}$.

### *A. Example 1*

In this numerical example, the performance of the proposed PCA will be compared with the performance of no power control (NPC) at all (fixed transmitted power).

Using the above cellular model features, the mean reverting PL $X(t,\tau)$, velocity and distance as a function of time for one of the mobiles chosen at random is shown in Fig. 3.

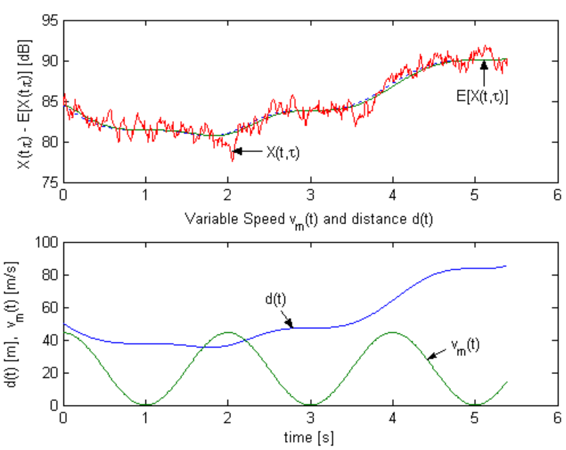
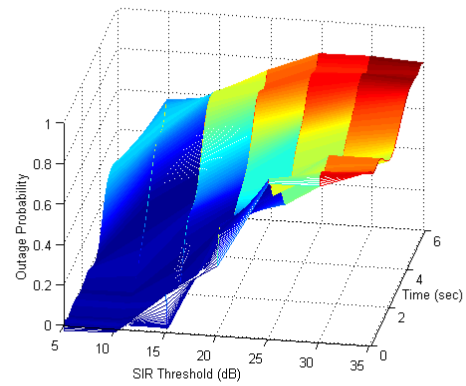
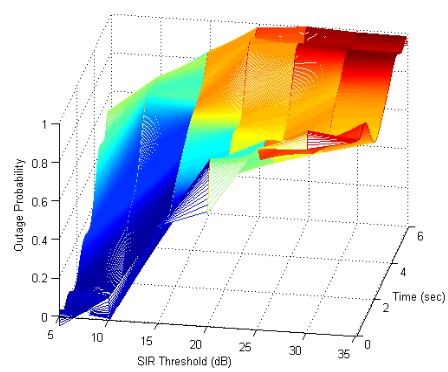



Fig. 3: Mean-reverting PL $X(t,\tau)$ for a mobile in Example 1. The mobile starting at 50 meters from its base station with angle of 135 degree and sinusoidal speed with average 80 km/hr (22.2 m/s).

The SIR threshold $\overline{\gamma}_{th}$ is varied from five to thirty five in steps of five, and for each value of $\overline{\gamma}_{th}$ the outage probability is computed every 15 millisecond for 5 seconds. The outage probability is computed using Monte-Carlo simulations. The outage probability graphs of this example for both the PC and NPC cases are shown in Fig. 4a and 4b respectively. Fig. 4 shows how the outage probability changes with respect to SIR threshold ($\overline{\gamma}_{th}$) and time. As the $\overline{\gamma}_{th}$ increases, the outage probability also increases. This is obvious since we expect more users to fail as $\overline{\gamma}_{th}$ increases. The outage probability is also changing with respect to time. This is because the mobiles are moving in different directions with different velocities. At any time, some mobiles are moving towards their own base stations and others are moving away from their own base stations.




(a)




(b)

Fig. 4: Outage probability for dynamical lognormal fading model in Example 1. (a) Using PPCS algorithm. (b) Using no power control (NPC).

The average outage probability over all time intervals is shown in Fig. 5. The outage probability is drawn versus $\overline{\gamma}_{th}$, which varies from 5 to 20 dB. The performance of PPCS is compared with the performance of NPC. Results show that the PPCS algorithm outperforms the reference algorithm by an order of magnitude. At outage probability below 0.2, SIR gains in excess of 10 dB may be achieved. The objective of PPCS algorithm is to minimize the total transmitted power such that the SIR of all users is achieved.

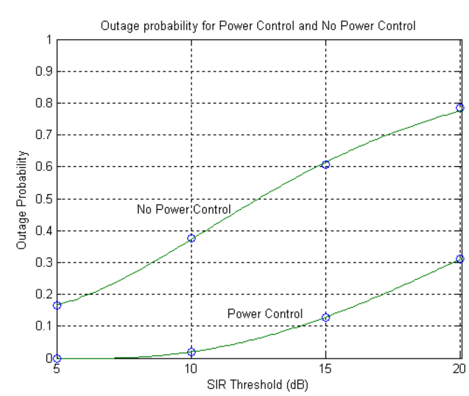



Fig. 5: Average outage probability for dynamical lognormal fading model in Example 1. Performance comparison.

*B. Example 2*

In this example, the effect of velocity on the performance of dynamical wireless network will be determined. All the parameters in this example are the same as the ones in the previous example except the velocities of mobiles. All mobiles are assumed to have the same average velocity of 60 km/hr for case 1 and 120 km/hr for case 2.

The outage probability for different velocities (60 km/hr and 120 km/hr) is calculated and the average outage probability over all time intervals is shown in Fig. 6. The performance of PPCS at 60 km/hr is better than the one at 120 km/hr. The increase in velocity affects the value of the PL in the spatial-temporal model. An increase in the velocity of a mobile causes an increase in the PL. Also there are faster changes in the dynamical wireless channel at 120 km/hr than at 60 km/hr. Therefore, higher velocities reflect higher values of probability of outage.

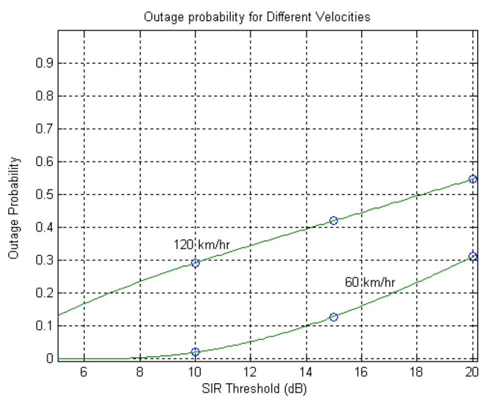



Fig. 6: Average outage probability for dynamical lognormal fading model in Example 2. Different velocities comparison.

## V. CONCLUSIONS

PPCS power control scheme as developed in [16] is applied to dynamical lognormal wireless communication channel models. More realistic time-varying wireless channel models are used. The dynamics of the channel are depicted by SDE's, which essentially capture the spatial-temporal variations of wireless fading communication networks. The optimization problem is solved by linear programming. Iterative algorithms can be used to solve for the optimization problem. The performance measure is interference or outage probability. Numerical results presented for this algorithm show that there are potentially large gains to be achieved by using PC. Gains in excess of 10 dB in interference reduction may be achieved. This would correspond to capacity gains in the order of 4 compared to systems using fixed transmitter power. Velocities of mobiles affect the performance of wireless systems. Higher speeds result in higher outage probabilities and therefore lower performance. The numerical results presented for lognormal fading indicate that the performance of this algorithm is close to the optimal case as long as the channel model does not change significantly.

## REFERENCES


[1] S. Grandhi, R. Vijayan and D. Goodman and J. Zander, "Centralized power control in cellular radio systems", *IEEE Trans. on Vehicular Tech.*, vol. 42, no.4, Nov. 1993.

[2] J. Zander, "Performance of optimum transmitter power control in cellular radio systems", *IEEE Trans. on Vehicular Tech*., vol. 41, no.1, Feb. 1992.

[3] J. Aein, "Power balancing in systems employing frequency reuse", *COMSAT Technical Review*, vol. 3, 1973.

[4] H. Alavi and R. Nettleton, "Downstream power control for spread spectrum cellular mobile radio system", *Proceedings of IEEE Global Telecommunications Conference*, Nov. 1982.

[5] Q. Wu, "Performance of optimum transmitter power control in CDMA cellular mobile systems", *IEEE Transactions on Vehicular Technology*, vol. 48, no. 2, March 1999.

[6] S. A. Grandhi, J. Zander and R. Yates, "Constrained power control", *Wireless Personal Communications*, vol. 2, no. 3, Aug. 1995.

[7] N. Bambos and S. Kandukuri, " Power-controlled multiple access schemes for next-generation wireless packet networks", *IEEE Wireless Communications*, vol. 9, issue 3, June 2002.

[8] X. Li and Z. Gajic, "An improves SIR-based power control for CDMA systems using Steffensen iterations", *Proceeding of the Conference on Information Science and Systems*, Mar. 2002.

[9] G. J. Foschini and Z. Miljanic, "A simple distributed autonomous power control algorithm and its convergence", *IEEE Trans. on Vehicular Tech*., vol. 42, no.4, Nov. 1993.

[10] S. Kandukuri and S. Boyd, "Optimal power control in interference-limited fading wireless channels with outage-probability specifications", IEEE Transactions on Wireless Communications, vol. 1, no. 1, pp. 46-55, 2002.

[11] N. Bui and S. Dey, "Optimal power control in CDMA over markov fading channels", in Proc. IEEE International Symposium in Information Theory, (Lausanne, Switzerland), pp. 79, July 2002.

[12] S. Koskie and Z. Gajic, "Optimal SIR-based power control in 3G wireless CDMA networks", *Proceedings of the American Control Conference*, vol. 2, Jun. 2003.

[13] C.D. Charalambous and N. Menemenlis, "State space approach in modeling multipath fading channels: stochastic differential equations and Ornstein-Uhlenbeck process" in *Proc. of IEEE ICC 2001*, Finland, Helsinki, June 11-15, 2001.

[14] C.D. Charalambous and N. Menemenlis, "Temporal and spatial lognormal shadowing models using stochastic differential equations", *IEEE Trans on Communications Systems* (preprint) 2002.

[15] C.D. Charalambous and N. Menemenlis, "Stochastic models for long term Multipath fading channels", 38th *IEEE Conference on Decision and Control* (CDC), 5:4947-4952, Dec. 1999.

[16] C. D. Charalambous, S. Djouadi, S. Denic and N. Menemenlis, "Stochastic power control for short term flat fading networks: Almost sure QoS measures", in *Proceedings of the 40th IEEE Conference on Decision and Control,* pp. 1049-1052, Dec. 2001.

[17] C.D. Charalambous and N. Menemenlis, "General non-stationary models for short term and long term fading channels", *EUROCOMM 2000*, pp. 142-149, April 2000.

[18] J. G. Proakis. "*Digital communications*", McGrow-Hill, NY, 1989.

[19] T.S. Rappaport, Wireless Communications. Prentice Hall, 1996.

[20] F. Graziosi, M. Pratesi, M. Ruggieri, and F. Santucci, "A multicell model of handover initiation in mobile cellular networks", *IEEE Transactions on Vehicular Technology*, vol. 48 (3): pp. 802-814, 1999.

[21] F. Graziosi and F. Santucci, "A general correlation model for shadow fading in mobile systems", *IEEE Communication Letters*, vol. 6(3), pp. 102-104, 2002.

[22] M. Taaghol and R. Tafazolli, "Correlation model for shadow fading in land-mobile satellite systems", *Electronics Letters*, vol. 33(15), pp.1287-1288, 1997.