An Efficient Multiobjective Power Control Algorithm for Wireless CDMA Networks

M. Rezayi[1], H. Farrokhi[2]

Abstract

This paper presents a multiobjective power control algorithm that updates the transmitted power based on local information. The proposed algorithm is expanded by using multiobjective optimization schemes. The objectives to be optimized in this paper are determined so as to reduce the SINR fluctuations as well as maintaining the SINR to an acceptable level with minimizing an average transmitted power. The convergence properties of the proposed algorithm are studied theoretically and with numerical simulations. The results indicate that the algorithm converges more rapidly and has lower average transmitted power than other existing algorithms. The current study also suggests a practical version of the proposed algorithm and compares it to the existing totally distributed bang-bang power control (B-BPC) or fixed step power control (FSPC) and multiobjective totally distributed power control (MOTDPC) algorithms. Numerical results show that the proposed algorithm is potentially much more efficient in terms of convergence speed and average consumption power than the other two algorithms.

Keywords: Distributed Power Control, Multiobjective Optimization, Cellular Systems, CDMA, Convergence.

1. Introduction

Power control (PC) plays an important role in mobile cellular systems' design. The objective is to manage mutual interference so that every user can have an acceptable link quality. Usually, the link quality (also called quality of service, QoS) is measured by the signal-to interference plus noise ratio (SINR). In recent decades, many researchers have investigated the PC problem wioth different perspectives. Especially, the PC in cellular radio systems has drawn much attention since Zander's work in [1] and [2] on centralized and distributed SINR balancing. The SINR balancing was further investigated by Grandhi et al. in [3] and [4]. In [5], Foschini and Miljanic considered a more general and realistic model, in which a positive receiver noise and a respective target SINR were taken into account. Foschini and Miljanic's distributed algorithm (FMA) was shown to converge, either synchronously or asynchronously as defined in [6], to a fixed point of a feasible system. Based on the FMA, in [7] Grandhi and Zander suggested a distributed constrained PC (DCPC) scheme, in which an upper limit for transmitted power was considered. Their work, i.e. the DCPC algorithm, has become one of the most widely accepted algorithms by the academic community. Meanwhile, in [8], a framework on the convergence of the generalized uplink PC was provided by Yates and extended by Huang and Yates in [9]. The results of their work could present a framework for designing and analyzing new algorithms. Moreover, some second-order PC algorithms requiring power levels of current and previous iterations have been proposed in [10] and [11] to enhance the convergence speed of the PC. In [12], Uykan and Koivo developed a nonlinear distributed PC algorithm whose convergence toward the optimum power vector was twice as fast as the DCPC algorithm. Also in [13], they proposed an algorithm with similar formulation that established a connection between link gains and algorithm parameters. In continuation, they utilized the systems control theory with variable structures to solve the PC problem by designing a controller having minimum sensitivity to the unknown link gain variations; [see 14]. A statistical distributed PC algorithm proposed in [15] assumes noisy values for the measured SINR and minimizes the total variance of the mobiles transmitted powers and the SINR errors. The gain and interference variation issues have been considered in [16], wherein the corresponding algorithm estimates very small variations of the channel and achieves the desired SINR level for any user.

Multiobjective optimization (MO) method with capability to optimize two or more objectives has been proposed in [17]-[18]. This method is applied to find the optimal solution, which is a compromise between multiple and contradicting objectives. It is noteworthy here to mention the differences between joint optimization and MO optimization. In joint optimization, it is not necessary for the objectives to be contradicting.

1. Department of Electrical Engineering, University of Birjand, Birjand, Iran. m_rezaie_2005@yahoo.com.
2.Assistant professor Department of Electrical Engineering, University of Birjand, Iran.hfarrokhi@birjand.ac.ir.

Furthermore, in joint optimization we are usually interested in one optimal solution which could be a global or a local extreme point of the combined objective function. In the MO method, we are more interested in the Pareto optimal set which containsallnon-inferior solutions. The decision maker can then select the most preferred solution out of the Pareto optimal set. The weighted sum method to handle the MO applied in this paper is structurally similar to the joint optimization.

Here, the proposed algorithm aims to achieve three objectives by applying the MO method. The first is the minimization of transmitted power. Achieving an acceptable QoS (in terms of SINR) is the second objective and the third objective is to minimize the SINR fluctuations. Performance evaluation simulations confirm that our algorithm has the highest convergence speed and the lowest average transmitted power among other existing distributed algorithms.

The rest of the paper is organized as follows: Section 2 describes the MO method and its application in the PC problem. Sections 3 and 4 analyze the convergence characteristics of the original and the practical version of the proposed PC algorithm, respectively, and Section 5 deals with the numerical results and performance evaluation/ comparison of the proposed PC algorithm. The paper is concluded in Section 6.

2. MIDPC Algorithm

The MO optimization approach is a technique that is used to optimize a number (≥2) of different objectives which might, in general, be incommensurable. In this technique, we optimize a vector, rather than a scalar, of objective functions each of which is a function of a decision vector (variable) [20]. The mathematical form of the MO optimization is

$$\begin{aligned}&\min\left\{f_1(\mathrm{x}),\ f_2(\mathrm{x}),\ \ldots\ ,f_m(\mathrm{x})\right\}\\&\text{subject to } \mathrm{x}\in\mathbf{S}\end{aligned}\qquad(1)$$

where $m\geq 2$ that is more than 2 objectives are to be optimized, $f_i:\Re^n\rightarrow\Re$, $i=0,1,2,\ldots,m$ are the objective functions, and x is the decision vector (variable) in feasible region $\mathbf{S}$, which is a subset of the space $\Re^n$ made by the decision vectors. The abbreviated min{•} represents the function whereby we aim to simultaneously minimize all the objectives. Since the objectives can generally be either conflicted or incommensurable, there will be no single solution, which means that there will be no single vector to optimize all objectives at the same time. As mentioned earlier, in solving the MO problem, we may have different optimal solutions from different points of view. They are called Pareto optimal solutions and the set containing all solutions is called Pareto optimal set.

After generating the Pareto set, our attempt is usually to obtain one solution of the Pareto optimal set which is selected by the problem maker or a decision maker. There are different approaches to solve the MO problem. One is to exploit soft-computing methods such as genetic algorithms [21]. In this paper we concentrate on the analytical solutions of the MO problem. One interesting and useful method which is particularly applied to the MO optimization in radio resources management (RRM) is the method of weighted metrics [20]. In cases where the desired optimal solutions of the objectives are known in advance, the MO problem defined in (1) can be rewritten as

$$\begin{aligned}&\min\left(\sum_{i=1}^{m}\lambda_i\left|f_i(\mathrm{x})-z_i^*\right|^{\mathrm{p}}\right)^{\frac{1}{\mathrm{p}}}\\&\text{subject to } \mathrm{x}\in\mathbf{S},\end{aligned}\qquad(2)$$

in which $1\leq\mathrm{p}\leq\infty$, z_i^* is the desired solution of the objective *i*, e. g., the supremum SINR, which is denoted hereafter by Γ_i^{sup}, and $\lambda_i\geq 0$ is the tradeoff factor for the objective *i*, such that $\sum_{i=1}^{m}\lambda_i=1$. The PC problem in this paper will be formulized by the following three objectives:

1. Minimizing the transmitted powers of all transmitters.
2. Maintaining the SINR as close as possible to the supremum SINR for all transmitters.
3. Reducing the SINR fluctuations (see [19]).

It should be noted that the supremum SINR is not usually a fixed value and that it contains a margin which lies between the supremum and the minimum desired SINRs. Hence, any value of the SINR which falls inside the margin is considered as an accepted SINR. Fig. 1 illustrates this idea for a 2-user case. The solid lines correspond to the power values for which the SINR is equal to the minimum desired level while the dashed lines correspond to the power values for which the SINR yields its supremum level.

The mathematical interpretation of the preceding three objectives for user i can be defined as the following error function

$$e_i(t) = \lambda_{i,1}\left|p_i(t) - p_{i,min}\right| + \lambda_{i,2}\left|\Gamma_i(t) - \Gamma_i^{\sup}\right| + \lambda_{i,3}\left|\Gamma_i(t) - \Gamma_i(t\text{-}1) - \beta\Gamma_i^{\sup}\right| \quad (3)$$

in which $\lambda_{i,1}$, $\lambda_{i,2}$ and $\lambda_{i,3}$ are tradeoff factors such that $\lambda_{i,1} + \lambda_{i,2} + \lambda_{i,3} = 1$ and $\lambda_{i,1}, \lambda_{i,2}, \lambda_{i,3} \geq 0$, $\Gamma_i^{\sup}$ is the supremum SINR, $p_i(t)$ and $p_{i,\min}$ are user i's instantaneous and minimum transmitted powers, respectively. Generally, each user can have different values of tradeoff factors as well as the supremum SINR. In (3), $\Gamma_i(t)$ is the SINR of user i at a time slot t and is given by

$$\Gamma_i(t) = \frac{g_{ii}(t)\, p_i(t)}{\sum_{\substack{j=1 \\ j\neq i}}^{Q} g_{ij}(t)\, p_j(t) + \nu_i(t)}, \qquad i = 1,2,\ldots,Q \quad (4)$$

where $g_{ij}(t)$ represents the channel gain between transmitter i and receiver j, Q is the number of active users, and $\nu_i(t)$ is the average noise power, all at time slot t. It is assumed that the user i is assigned to the base station i. Also, transmitted data from a user is acceptable in a receiver as long as the received SINR is greater than the minimum SINR denoted by $\Gamma_{i,\min}$. Otherwise, that user is either disconnected from its base station or handed over to another base station.

To generalize the optimization problem over all users for $\boldsymbol{N}$ time slots, we define the problem in terms of finding the minimum of the cost function as in [18] to be

$$J(\mathbf{p}(t)) = \left[\sum_{i=1}^{Q}\sum_{t=1}^{\boldsymbol{N}} \gamma^{\boldsymbol{N}\text{-}t} e_i^2(t)\right], \qquad t = 1,2,\ldots,\boldsymbol{N} \quad (5)$$

with respect to the power vector $\mathbf{P} = [p_1, p_2, \cdots, p_Q]^T$, in which the superscript T stands for transpose and γ is an adaptation factor. The problem stated by (5) is a nonlinear optimization problem due to the use of the absolute value function in (3). One advantage of using the cost function in (5) is that it could be used for different purposes, such as reducing the transmitted power, achieving the supremum SINR, reducing the SINR fluctuations, increasing the system throughput, reducing the pocket delay, etc.

The first term in (3) does not require the absolute value function since the transmitted power cannot be less than $p_{i,\min}$. As a result, the error function is improved as

$$e_i(t) = \lambda_{i,1}\left(p_i(t) - p_{i,min}\right) + \hat{\lambda}_{i,2}(t)\left(\Gamma_i(t) - \Gamma_i^{\sup}\right) + \hat{\lambda}_{i,3}(t)\left(\Gamma_i(t) - \Gamma_i(t\text{-}1) - \beta\Gamma_i^{\sup}\right)$$
$$t = 0, 1, 2, \ldots, \; i = 1, 2, \ldots, Q \quad (6)$$

where $\hat{\lambda}_{i,2}(t) = sign\left(\Gamma_i(t) - \Gamma_i^{\sup}\right)\lambda_{i,2}$ and $\hat{\lambda}_{i,3}(t) = sign\left(\Gamma_i(t) - \Gamma_i(t\text{-}1) - \beta\Gamma_i^{\sup}\right)\lambda_{i,3}$.

Assume that the power $p_i(t)$ is expressed by a linear autoregressive model [22], as shown in Fig. 2. So, the transmitted power by the user i is given by

$$p_i(t) = \sum_{k=1}^{n} w_i(k) p_i(t\text{ - }k) = \mathbf{w}_i^T \mathrm{X}_i(t), \qquad t = 0,1,2,\ldots$$

in which

$$\mathbf{w}_i = [w_i(1)\ldots w_i(n)]^T, \qquad \mathbf{X}_i(t) = [p_i(t\text{ - }1)\ldots p_i(t\text{ - }n)]^T$$

where $\mathbf{w}_i$ is the power adaptation weight vector, $\mathbf{X}_i$ contains all previously known transmitted powers, and n is the number of taps. Substituting (7) into (6), we obtain

$$e_i(t) = \lambda_{i,1}\left(\mathbf{w}_i^T\mathbf{X}_i(t) - p_{i,min}\right) + \hat{\lambda}_{i,2}(t)\left(\frac{g_{ii}(t)\,\mathbf{w}_i^T\mathbf{X}_i(t)}{I_i(t)} - \Gamma_i^{\sup}\right)$$
$$+\hat{\lambda}_{i,3}(t)\left(\frac{g_{ii}(t)\,\mathbf{w}_i^T\mathbf{X}_i(t)}{I_i(t)} - \frac{g_{ii}(t)\,\mathbf{w}_i^T\mathbf{X}_i(t\text{ - }1)}{I_i(t)} - \beta\Gamma_i^{\sup}\right)$$

and by letting

$$\alpha_{1t} = \left[\lambda_{i,1} + \hat{\lambda}_{i,2}(t)\frac{g_{ii}(t)}{I_i(t)} + \hat{\lambda}_{i,3}(t)\frac{g_{ii}(t)}{I_i(t)}\right], \qquad \alpha_{2t} = -\hat{\lambda}_{i,3}(t)\frac{g_{ii}(t)}{I_i(t)}$$

then, (9) can be rewritten as

$$e_i(t) = \alpha_{1t}\mathbf{w}_i^T\mathbf{X}_i(t) + \alpha_{2t}\mathbf{w}_i^T\mathbf{X}_i(t\text{ - }1) - \lambda_{i,1}p_{i,min} - \hat{\lambda}_{i,2}(t)\Gamma_i^{\sup} - \hat{\lambda}_{i,3}(t)\beta\Gamma_i^{\sup}$$

As a result, minimizing (5) with respect to p_i is equivalent to its minimization with respect to the vector $\mathbf{w}$. The necessary condition for minimizing (5) for all i is

$$2\sum_{t=1}^{\boldsymbol{N}} \gamma^{\boldsymbol{N}\text{-}t} e_i(t)\frac{\partial e_i(t)}{\partial \mathbf{w}} = 0$$

From (11) we have

$$\frac{\partial e_i(t)}{\partial \mathbf{w}} = \alpha_{1t}\mathbf{X}_i^T(t) + \alpha_{2t}\mathbf{X}_i^T(t\text{ - }1)$$

Substituting (11) and (13) into (12), we obtain

$$\sum_{t=1}^{\boldsymbol{N}} \gamma^{\boldsymbol{N}\text{-}t} e_i(t)\frac{\partial e_i(t)}{\partial \mathbf{w}} = \sum_{t=1}^{\boldsymbol{N}} \gamma^{\boldsymbol{N}\text{-}t}\left(\alpha_{1t}\mathbf{w}_i^T\mathbf{X}_i(t) + \alpha_{2t}\mathbf{w}_i^T\mathbf{X}_i(t\text{ - }1) - \lambda_{i,1}p_{i,min}\right.$$
$$\left. - \hat{\lambda}_{i,2}(t)\Gamma_i^{\sup} - \hat{\lambda}_{i,3}(t)\beta\Gamma_i^{\sup}\right)\left(\alpha_{1t}\mathbf{X}_i^T(t) + \alpha_{2t}\mathbf{X}_i^T(t\text{ - }1)\right) = 0$$

and solving (14) for $\mathbf{w}_i$ results in

$$\left\{\sum_{t=1}^{N}\gamma^{N-t}\left(\alpha_{1t}^{2}\mathbf{X}_i(t)\mathbf{X}_i^T(t)+\alpha_{1t}\alpha_{2t}\mathbf{X}_i(t)\mathbf{X}_i^T(t-1)+\alpha_{2t}\alpha_{1t}\mathbf{X}_i(t-1)\mathbf{X}_i^T(t)+\alpha_{2t}^{2}\mathbf{X}_i(t-1)\mathbf{X}_i^T(t-1)\right)\right\}\mathbf{w}_i$$
$$=\sum_{t=1}^{N}\gamma^{N-t}\left(\lambda_{i,1}p_{i,min}+\hat{\lambda}_{i,2}(t)\Gamma_i^{sup}+\hat{\lambda}_{i,3}(t)\beta\Gamma_i^{sup}\right)\times\left(\alpha_{1t}\mathbf{X}_i^T(t)+\alpha_{2t}\mathbf{X}_i^T(t-1)\right).$$

To facilitate operations, we assume $n=1$ (one time slot) in (7) and $\gamma=0$ in (15). Using these assumptions in solving (15) we find

$$\mathbf{w}_i=\frac{\lambda_{i,1}p_{i,min}+\left(\hat{\lambda}_{i,2}(t)+\beta\hat{\lambda}_{i,3}(t)\right)\Gamma_i^{sup}}{\lambda_{i,1}p_i(t-1)+\left(\hat{\lambda}_{i,2}(t)+\hat{\lambda}_{i,3}(t)\right)\Gamma_i(t-1)-\hat{\lambda}_{i,3}(t)\Gamma_i(t-2)}\qquad t=0,1,2,\ldots;\quad i=1,\ 2,\ \ldots,\ Q$$

and the transmitted power by the user i at time slot t is given by

$$p_i(t)=\left(\frac{\lambda_{i,1}p_{i,min}+\left(\hat{\lambda}_{i,2}(t)+\beta\hat{\lambda}_{i,3}(t)\right)\Gamma_i^{sup}}{\lambda_{i,1}p_i(t-1)+\left(\hat{\lambda}_{i,2}(t)+\hat{\lambda}_{i,3}(t)\right)\Gamma_i(t-1)-\hat{\lambda}_{i,3}(t)\Gamma_i(t-2)}\right)p_i(t\text{-}1)\qquad t=0,1,2,\ldots;\quad i=1,\ 2,\ \ldots,\ Q\ .$$

Since $\hat{\lambda}_{i,2}(t)$ and $\hat{\lambda}_{i,3}(t)$ change rapidly with time, the transmitted power in (17) may take negative values, which is practically not feasible. To cope with this issue, only positive values of $\hat{\lambda}_{i,2}(t)$ and $\hat{\lambda}_{i,3}(t)$ are taken into account, e.g. $\hat{\lambda}_{i,2}(t)=\lambda_{i,2}$ and $\hat{\lambda}_{i,3}(t)=\lambda_{i,3}$. It is worth to mentioning that these assumptions can slightly lower the convergence speed of the proposed algorithm however, on the other hand, they simplify the algorithm significantly. Fig. 3 depicts the effects of these simplifications on the performance of the proposed algorithm. This figure is obtained from the numerical results of simulations for the static channel in Sec. V. Accordingly, the iterative form of the proposed distributed PC algorithm, called here as the *Multiobjective Improved Distributed PC* (MIDPC) algorithm, can be simplified as

$$p_i(t)=\left(\frac{\lambda_{i,1}p_{i,min}+\left(\lambda_{i,2}+\beta\lambda_{i,3}\right)\Gamma_i^{sup}}{\lambda_{i,1}p_i(t-1)+\left(\lambda_{i,2}+\lambda_{i,3}\right)\Gamma_i(t-1)-\lambda_{i,3}\Gamma_i(t-2)}\right)p_i(t\text{-}1)\qquad t=0,1,2,\ldots;\quad i=1,\ 2,\ \ldots,\ Q$$

It can be readily seen that the substitutions $\lambda_{i,1}=\lambda_{i,3}=0$, $\lambda_{i,2}=1$ and $\lambda_{i,3}=0$ in (18) lead to the distributed power control (DPC) and the multiobjective distributed power control (MODPC) algorithms, respectively, i.e., the DPC and the MODPC algorithms are both special cases of our MIDPC algorithm. Moreover, for $\lambda_{i,2}=\lambda_{i,3}=0$, $\lambda_{i,1}=1$ the mobiles will transmit with their minimum power regardless of their SINR values (no PC).

With the consideration of constraint maximum power, the MIDPC algorithm defined by (18) can be modified as

$$p_i(t)=\min\left\{p_{i,max},\left(\frac{\lambda_{i,1}p_{i,min}+\left(\lambda_{i,2}+\beta\lambda_{i,3}\right)\Gamma_i^{sup}}{\lambda_{i,1}p_i(t-1)+\left(\lambda_{i,2}+\lambda_{i,3}\right)\Gamma_i(t-1)-\lambda_{i,3}\Gamma_i(t-2)}\right)p_i(t\text{-}1)\right\}\qquad t=0,1,2,\ldots;\quad i=1,\ 2,\ \ldots,\ Q\ .$$

It is interesting to note that the transmitted power of the MIDPC algorithm in (18) is naturally upper- bounded by

$$p_i(t)\le p_{i,min}+\frac{\left(\lambda_{i,2}+\beta\lambda_{i,3}\right)}{\lambda_{i,1}}\Gamma_i^{sup}\qquad ,i=1,2,\ldots,Q$$

In the following section, we discuss the convergence characteristics of our proposed MIDPC algorithm.

3.Convergence Analysis of the MIDPC algorithm

To proceed with the convergence analysis of the MIDPC algorithm, we use the following definitions made by Yates [8] and important theories therein.

Definition 1: The mapping function, $\mathcal{I}(\mathbf{P})$, of PC is called a standard interference function if, for any $\mathbf{P}\ge 0$, it satisfies the following conditions:

1. Positivity, i.e., $\mathcal{I}(\mathbf{P})\ge 0$;
2. Monotonicity, that is if $\mathbf{P}_1\le\mathbf{P}_2$ then $\mathcal{I}(\mathbf{P}_1)\le\mathcal{I}(\mathbf{P}_2)$;
3. Scalability, which means that for all $\alpha>1$ and $\alpha\in\Re$, $\alpha\mathcal{I}(\mathbf{P})>\mathcal{I}(\alpha\mathbf{P})$.

Any PC algorithm whose $\mathcal{I}(\mathbf{P})$ is standard, is called standard PC algorithm.

Definition 2 (feasibility): The network configuration is said to be feasible if the largest eigenvalue of the normalized link-gain matrix $\mathbf{H}$, $\rho(\mathbf{H})<1$.

Theorem 1: For a network configuration, if the PC problem is feasible, then for any initial power vector $\mathbf{P}(0)$, the synchronous/asynchronous standard PC algorithm converges to a fixed point (vector) $\mathbf{P}^*$.

Now, we discuss the convergence analysis of the MIDPC algorithm by exploiting the following two propositions and their proofs:

Proposition 1: In a static channel, for any non-negative initial power vector, $\mathbf{P}(0)$, the MIDPC algorithm specified by (18) converges to a unique fixed point determined by the value of tradeoff factors.

Proof: In order to prove this proposition, it suffices to prove that the MIDPC algorithm is a standard PC algorithm. The standard interference

function, $\mathcal{I}_i\left(\mathbf{P}\left(t\right)\right)$, of the MIDPC algorithm for the
us

$$\mathcal{I}_i\left(\mathbf{P}(t)\right)=\left(\frac{\lambda_{i,1}p_{i,min}+\left(\lambda_{i,2}+\beta\lambda_{i,3}\right)\Gamma_i^{\sup}}{\lambda_{i,1}p_i\left(t\text{-}1\right)+\left(\lambda_{i,2}+\lambda_{i,3}\right)\Gamma_i\left(t\text{-}1\right)-\lambda_{i,3}\Gamma_i\left(t\text{-}2\right)}\right)P_i\left(t\text{-}1\right)$$
$$t=0,1,2,\ldots;\quad i=1,\ 2,\ \ldots,\ Q\,.$$

er i, is given by

By defining the normalized interference function as

$$I_i\left(t\right)=\sum_{\substack{j=1\\ j\neq i}}^{Q}\frac{g_{ij}\left(t\right)p_j\left(t\right)}{g_{ii}\left(t\right)}+\frac{\nu_i\left(t\right)}{g_{ii}\left(t\right)}$$

and eliminating t for convenience, we can rewrite (21) in the form

$$\mathcal{I}_i\left(\mathbf{P}\right)=\frac{aI_i\left(\mathbf{P}\right)}{\lambda_{i,1}I_i\left(\mathbf{P}\right)+\lambda_{i,2}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\mathbf{P}\right)}{\mathbf{P}_{=i}}}$$

where $a=\lambda_{i,1}p_{i,min}+\left(\lambda_{i,2}+\beta\lambda_{i,3}\right)\Gamma_i^{\sup}$ and $\mathbf{P}_{=i}=p_i$. Moreover, from (22) it is apparent that for any

$$\mathbf{P}\geq 0\ \Rightarrow\ I_i\left(\mathbf{P}\right)\geq 0,\qquad\forall i=1,2,\ldots,Q$$

Also if

$$\mathbf{P}\geq\mathbf{Z}\ \Rightarrow\ I_i\left(\mathbf{P}\right)\geq I_i\left(\mathbf{Z}\right),\qquad\forall i=1,\ 2,\ \ldots,\ Q$$

Since $\lambda_{i,1},\lambda_{i,2},\lambda_{i,3}\geq 0$ and $\beta>0$, then from (23) and (24) we obtain

$$\mathbf{P}\geq 0\ \Rightarrow\ \mathcal{I}_i\left(\mathbf{P}\right)\geq 0,\qquad\forall i=1,2,\ldots,Q$$

which concludes the positivity proof.

The monotonicity criterion is proved here using contradiction. Suppose that for any $\mathbf{P}\geq\mathbf{Z}$, $I_i\left(\mathbf{P}\right)<I_i\left(\mathbf{Z}\right)$, $\forall i=1,2,\ldots,Q$. Then from (23) we find that

or

$$aI_i\left(\mathbf{P}\right)<aI_i\left(\mathbf{P}\right)\frac{\left[\lambda_{i,1}I_i\left(\mathbf{Z}\right)+\lambda_{i,2}\dfrac{I_i\left(\mathbf{Z}\right)}{I_i\left(\mathbf{P}\right)}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\mathbf{Z}\right)}{\mathbf{P}_{=i}}\right]}{\lambda_{i,1}I_i\left(\mathbf{Z}\right)+\lambda_{i,2}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\mathbf{Z}\right)}{\mathbf{Z}_{=i}}}$$

where $\mathbf{Z}_{=i}=z_i$. From (25), however, we have

$$0<\frac{\left[\lambda_{i,1}I_i\left(\mathbf{Z}\right)+\lambda_{i,2}\dfrac{I_i\left(\mathbf{Z}\right)}{I_i\left(\mathbf{P}\right)}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\mathbf{Z}\right)}{\mathbf{P}_{=i}}\right]}{\lambda_{i,1}I_i\left(\mathbf{Z}\right)+\lambda_{i,2}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\mathbf{Z}\right)}{\mathbf{Z}_{=i}}}<1$$

which contradicts with (28). As a result, (27) is not true. Then, for any $\alpha>1$

$$\mathcal{I}_i\left(\mathbf{P}\right)\geq\mathcal{I}_i\left(\mathbf{Z}\right),\qquad\forall i=1,2,\ldots,Q$$

and the monotonicity condition has been proved. To prove the third condition, the following inequality should meet

$$\alpha\mathcal{I}_i\left(\mathbf{P}\right)\geq\mathcal{I}_i\left(\alpha\mathbf{P}\right),\qquad\forall\alpha>1$$

From (22) we have

$$\forall\alpha>1\ \Rightarrow\ \alpha I_i\left(\mathbf{P}\right)\geq I_i\left(\alpha\mathbf{P}\right),\qquad\forall i=1,2,\ldots,Q$$

and from (23)

$$\alpha\mathcal{I}_i\left(\mathbf{P}\right)=\frac{a\alpha I_i\left(\mathbf{P}\right)}{\lambda_{i,1}I_i\left(\mathbf{P}\right)+\lambda_{i,2}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\mathbf{P}\right)}{\mathbf{P}_{=i}}}$$

or

$$\mathcal{I}_i\left(\alpha\mathbf{P}\right)=\frac{aI_i\left(\alpha\mathbf{P}\right)}{\lambda_{i,1}I_i\left(\alpha\mathbf{P}\right)+\lambda_{i,2}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\alpha\mathbf{P}\right)}{\alpha\mathbf{P}_{=i}}}$$

If we substitute (33) and (34) into (31), we find

$$\frac{a\alpha I_i\left(\mathbf{P}\right)}{\lambda_{i,1}I_i\left(\mathbf{P}\right)+\lambda_{i,2}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\mathbf{P}\right)}{\mathbf{P}_{=i}}}\geq\frac{aI_i\left(\alpha\mathbf{P}\right)}{\lambda_{i,1}I_i\left(\alpha\mathbf{P}\right)+\lambda_{i,2}+\beta\lambda_{i,3}\Gamma_i^{\sup}\dfrac{I_i\left(\alpha\mathbf{P}\right)}{\alpha\mathbf{P}_{=i}}}$$

or

$$a\alpha\lambda_{i,1}I_i\left(\mathbf{P}\right)I_i\left(\alpha\mathbf{P}\right)+a\alpha\lambda_{i,2}I_i\left(\mathbf{P}\right)+a\alpha\beta\lambda_{i,3}\Gamma_i^{\sup}I_i\left(\mathbf{P}\right)\frac{I_i\left(\alpha\mathbf{P}\right)}{\alpha\mathbf{P}_{=i}}$$
$$\geq a\lambda_{i,1}I_i\left(\mathbf{P}\right)I_i\left(\alpha\mathbf{P}\right)+a\lambda_{i,2}I_i\left(\alpha\mathbf{P}\right)+a\beta\lambda_{i,3}\Gamma_i^{\sup}I_i\left(\mathbf{P}\right)\frac{I_i\left(\alpha\mathbf{P}\right)}{\mathbf{P}_{=i}}.$$

Referring to (32), we can readily see that all the three terms in the left side of (36) are equal to or greater than their corresponding terms in the right side. Then, the scalability condition has also been proved. Now that we have all the three criteria satisfied, it can be said that our MIDPC algorithm is a standard interference function, i.e., it converges to a fixed point (vector) starting from any non-negative initial power vector.

Proposition 2: If the environment is noiseless, then for any $\mathbf{P}\left(0\right)>0$ and with appropriate selection of $\lambda_{i,1}$, $\lambda_{i,2}$ and $\lambda_{i,3}$ the proposed MIDPC algorithm converges to a balanced SINR such that

$$\lim_{t\to\infty}\mathbf{P}\left(t\right)=\mathbf{P}^*,\qquad t=0,1,2,\ldots;\quad i=1,2,\ldots,Q$$
$$\lim_{t\to\infty}\Gamma_i\left(t\right)=\mu^*,\qquad t=0,1,2,\ldots;\quad i=1,2,\ldots,Q$$

where μ^* is called the maximum achievable SINR and $\mathbf{P}^*$ is its corresponding eigenvector.

Proof: Since $\Gamma_i(t) = {p_i(t)}/{I_i(t,\mathbf{P})}$ where $I_i(t,\mathbf{P})$ is the normalized interference in (22) with $\nu_i(t) = 0$ for all users, then (18) can be expressed as

$$p_i(t+1) = \frac{a}{\lambda_{i,1} I_i(t) + \lambda_{i,2} + \beta\lambda_{i,3}\Gamma_i^{\sup}\frac{I_i(t)}{p_i(t)}} I_i(t) = \beta_i(t) I_i(t)$$

which has the form similar to the distributed PC algorithm in [4] where the rest of the proof can be found. Since the transmitted power from each user is upper-bounded as in (20), then the interference $I_i(t)$ will also be upper-bounded for all t. Thus for convergence, the tradeoff factors should be appropriately selected so that to satisfy the following condition

$$\lim_{t\to\infty} (\mu^*)^t \prod_{k=0}^{t} \left(\frac{a}{\lambda_{i,1} I_i(t) + \lambda_{i,2} + \beta\lambda_{i,3}\Gamma_i^{\sup}\frac{I_i(t)}{p_i(t)}} \right) < \infty$$

in which μ^* is the spectral radius of the channel gain matrix $\mathbf{H}$.

4. MITDPC Algorithm

So far, we have assumed that the MIDPC algorithm, similar to other distributed algorithms, has a perfect estimation of the mobile's SINR and updates the power using this information. In practical systems, however, only a quantized fraction (step) of the SINR in the form of one or two bits is available at the mobile stations in order to step up/down their transmitted power, accordingly. The practical replacement of the MIDPC algorithm, called *Multiobjective Improved Totally Distributed PC* (MITDPC) algorithm in this paper, improves the performance of the MIDPC algorithm even when the power update is accomplished based on a 1-bit command. We benefit from the 1-bit SINR estimation method used in [23] to evaluate the effects of quantization errors on our algorithm. Using the results of [23] we have

$$\tilde{\Gamma}_i(t) = \Gamma_i^{\sup} - \delta_i \left(\sum_{k=1}^{t-1} \upsilon_i(t-k) c_i(t,k) + \upsilon_i(t) \right) \qquad t = 0,1,2,\ldots; \quad i = 1,2,\ldots,Q,$$

where

$$\upsilon_i(t) = sign\left(\Gamma_i^{\sup} - \Gamma_i(t)\right) E_{\mathrm{pc},i}(t)$$

and

$$c_i(t,k) = \frac{1}{2^k} \prod_{n=0}^{k-1} [1 + \upsilon_i(t-n)\upsilon_i(t-n-1)]$$

In (41) the value of $E_{\mathrm{pc},i}(t)$ is 1 with probability $P_{PCE,i}(t)$ and -1 with probability $1 - P_{PCE,i}(t)$ where $P_{PCE,i}(t)$ is the bit error probability of the transmit power control (TPC) command. Therefore, the perfect SINR can be replaced in the MIDPC algorithm by the estimated SINR given by (40). The resulting MITDPC algorithm can then be stated by the following iterative expression for power as

$$p_i(t) = \left(\frac{\lambda_{i,1} p_{i,min} + (\lambda_{i,2} + \beta\lambda_{i,3})\Gamma_i^{\sup}}{\lambda_{i,1} p_i(t-1) + (\lambda_{i,2} + \lambda_{i,3})\tilde{\Gamma}_i(t-1) - \lambda_{i,3}\tilde{\Gamma}_i(t-2)} \right) p_i(t-1) \qquad t = 0,1,2,\ldots; \quad i = 1,2,\ldots,Q,$$

in which $\tilde{\Gamma}_i(t-1)$ and $\tilde{\Gamma}_i(t-2)$ are calculated from (40).

The MITDPC algorithm convergence analysis is presented in the following proposition and its proof.

Proposition 3: Starting from any initial power vector $\mathbf{P}(0) > 0$ for a static channel, the proposed MITDPC algorithm converges to a fixed point.

Proof: This proposition can be as easily proved as the proposition 1. Let's assume that the estimated SINR in (40) could be represented by

$$\tilde{\Gamma}_i(t) = \varepsilon_i(t)\Gamma_i(t)$$

where $\varepsilon_i(t) \geq 0$ is the estimated SINR error factor. Substituting (44) into (43), we obtain

$$\mathcal{I}_i(\mathbf{P}) = \left(\frac{\lambda_{i,1} p_{i,min} + (\lambda_{i,2} + \beta\lambda_{i,3})\Gamma_i^{\sup}}{\lambda_{i,1} p_i(t-1) + (\lambda_{i,2} + \lambda_{i,3})\varepsilon_i(t-1)\Gamma_i(t-1) - \lambda_{i,3}\varepsilon_i(t-2)\Gamma_i(t-2)} \right) p_i(t-1) \qquad t = 0,1,2,\ldots; \quad i = 1,2,\ldots,Q.$$

For a static channel, it may be assumed that $\varepsilon_i(t)$ remains unchanged during a PC time slot. In this case, we can improve and modify (23) for the MITDPC algorithm as

$$\mathcal{I}_i(\mathbf{P}) = \frac{a I_i(\mathbf{P})}{\lambda_{i,1} I_i(\mathbf{P}) + \tilde{\lambda}_{i,2} + \beta\tilde{\lambda}_{i,3}\Gamma_i^{\sup}\frac{I_i(\mathbf{P})}{\mathbf{P}_{=i}}}$$

where $\tilde{\lambda}_{i,2} = \varepsilon_i\lambda_{i,2}$ and $\tilde{\lambda}_{i,3} = \varepsilon_i\lambda_{i,3}$. Therefore, Proposition 3 can be proven in the same way as we did for proposition 1.

5. Numerical Results

Two different channel scenarios have been considered in the performance evaluation of the MIDPC algorithm. The first scenario assumes a static channel with additive Gaussian noise. Each user is assigned a base station with minimum path loss and the handover is assumed to be perfect. In the second scenario, the channel is dynamic with slow and fast fading and having almost the same parameters as in first scenario. In order to have an acceptable environment of simulation, the environment in [18] has been used, in which the minimum allowed SINR is 3 dB less than the supremum SINR. The supremum SINR is –18 dB for all users. The number of users in both scenarios is 120, which are uniformly distributed in an area of 4 km^2 with 4 base stations regularly distributed at (0.5, 0.5), (0.5, 1.5), (1.5, 0.5), and (1.5, 1.5) km coordinates. Moreover, the maximum transmitted power is limited and normalized to 30 dBm and the channel noise is Gaussian with zero mean and average power of –90 dBm.

The performance of the proposed algorithm with the other existing algorithms including the DCPC [7], FMA [5], CSOPC [10], and MODPC [18] algorithms have been evaluated in terms of error norm and outage percentage. The error norm is defined as the difference between the actual transmitted power in each time slot and the one in the optimized power vector obtained from the centralized PC algorithm. The outage percentage is obtained by calculating the time slots in which a user's SINR is less than the minimum desired SINR.

Results of the experiments indicate that with $\lambda_{i,1} = 0.028$, $\lambda_{i,2} = 0.97$, $\lambda_{i,3} = 0.002$, and $\beta = 0.25$, for all i, our algorithm achieves a good performance in terms of the convergence speed for both scenarios and, as a result, we have used these parameter values throughout simulations of our algorithm. Results of simulations for the MODPC in [18] have been obtained with $\lambda_{i,1} = 0.01$ and $\lambda_{i,2} = 0.99$.

Fig. 4 depicts the power convergence path trajectories corresponding to the DPC, MODPC, and MIDPC algorithms for a 2-user system. It is seen that the MIDPC algorithm is converging much faster than the two other algorithms toward feasible region.

As it was mentioned in previous section, the MIDPC algorithm attempts to find a power vector with an SINR between $\Gamma_{i,min}$ and Γ_i^{sup}. This is also the case for the MODPC algorithm. Fig. 5 illustrates the distinction between convergence points of the MODPC, the MIDPC, and the DPC algorithms. Although they all start from point (1), they converge to points (2), (3), and (4), respectively. The point (4) corresponds to Γ_i^{sup}.

In next simulation, we consider two mobiles that use the same channel. The average link gain g_{ij} is modeled as $g_{ij} = s_{ij}.d_{ij}^{-4}$, where s_{ij} is the shadow fading factor and d_{ij} is the distance between base station i and mobile j. The log-normally distributed s_{ij} is generated according to the model used in [25]. The DPC algorithm in [4] is chosen as the reference algorithm. The values of supremum SINR and receiver noise are selected as in [10] and [12] to be $\Gamma^{\text{sup}} = 6$ dB and $\nu = 0.1$, respectively. We define each normalized link gain as $h_{ij} = \left[\mathbf{H}\right]_{ij} = \Gamma_i^{\text{sup}}(g_{ij}/g_{ii})$, $h_{ii} = 0$, that changes with time around its mean value according to

$$h_{ij}\left(t\right) = \max\left\{0, h_{ij}^{av} + \Delta h_{ij}\left(t\right)\right\}$$

in which h_{ij}^{av} (known or estimated) is the mean value of the matrix $\mathbf{H}$ and $\Delta h_{ij}\left(t\right)$ (unknown) changes randomly at each iteration according to a given distribution. Without loss of generality, let us define maximum $\Delta h_{ij}\left(t\right)$ at time t as

$$\Delta_t = \max\left|\Delta h_{ij}\left(t\right)\right|$$

In this simulation $\Delta h_{ij}\left(t\right)$ in (47) is modeled as a uniformly distributed random variable with zero mean between $\left[-\Delta, +\Delta\right]$. The initial powers $p_i\left(0\right)$ were randomly chosen from the closed interval [0, 1]. We define the following average cost function for mobile i as in [13], which has the form

$$\varepsilon = \frac{1}{\text{KS}} \sum_{s=1}^{\text{S}} \sum_{k=1}^{\text{K}} \left(\Gamma_i^{\text{S}} - \Gamma_i^{\text{sup}}\right)^2$$

where S is the number of snapshots (during each snapshot a different feasible matrix $\mathbf{H}^{av}$ is randomly produced), and K is the number of steps for each snapshot. Fig. 6 shows the average costs (normalized with those of the MIDPC case) with respect to Δ_t / h_{ij}^{av} over 300 steps for 1000 different feasible average link gain matrices $\mathbf{H}^{av}$, i.e., S=1000 and K=300. The reason why, for very small link gain changes (i.e., $\Delta_t / h_{ij}^{av} < 0.1$) , the SINR variance is smaller in the DPC than that in the MIDPC is that, in the former case, the SINR values converge to the supremum SINR value whereas in the latter case, they converge to the interval between $\Gamma_{i,\min}$ and $\Gamma_i^{\sup}$. As expected, the MIDPC algorithm minimizes the SINR fluctuations.

This can be apparently found from Fig. 6. Also, as Δ_t increases ($\Delta_t / h_{ij}^{av} > 0.1$), the MIDPC algorithm exhibits more robust results than the DPC algorithm. Fig. 7 shows the evaluation of all these algorithms for static channel scenario. Compared to all the other depicted algorithms, it is apparently seen that the MIDPC algorithm has a good performance in terms of power convergence speed and outage percentage. Fig. 8 represents the performance of totally distributed FSPC, MOTDPC, and MITDPC algorithms. Since there is no access to exact SINR information in quantized distributed PC algorithms, then their performances degrade. As can be seen from Fig. 8, however, the proposed MITDPC algorithm still has a comparatively low outage percentage as well as a much higher convergence speed.

The average transmitted powers of the distributed PC and totally distributed PC algorithms are shown in Table 1. It is apparent that the proposed algorithm, in both the original (MIDPC) and the practical (MITDPC) versions, achieve lower average consumed power. For example, in the static channel scenario the average consumption power for the MIDPC algorithm is about 2.8 and 2 dBW less than the DCPC and the MODPC algorithms, respectively. Moreover, these power consumption improvements increase to about 8 and 2.5 dBW, respectively, for practical versions of these algorithms.

As mentioned earlier, the second objective of the proposed algorithm is to maintain the SINR at the acceptable level. Fig. 9 depicts the QoS in terms of the achieved SINR for the best and the worst situated users with the MIDPC algorithm. It is easily understood that the SINR achieves a level between $\Gamma_{i,min}$ and $\Gamma_i^{\sup}$.

To evaluate the performance of the algorithms in the dynamic scenario, we have considered the same environment as in the static scenario. The multipath fading has a Rayleigh distribution that is generated by a correlated process [24]. Also, the carrier frequency is 2 GHz and all the simulated algorithms assume the same mobile speed of 30 Km/h, which is acceptable in urban areas. Fig. 10 illustrates the evaluation results of all the simulated algorithms in dynamic scenario. Similar to the static scenario mentioned earlier, the MIDPC algorithm still outperforms the other algorithms in terms of the convergence speed and the outage percentage. It should be noted that the fluctuations in the outage percentage profile are due to the channel being dynamic.

Another performance characteristic of PC algorithms is the average power consumption in the dynamic scenario. Referring back to Table 1, we find that the MIDPC has apparently much lower average consumption power than that of other specified distributed algorithms. Besides, its practical version achieved best performance amongst others in terms of average consumption power. In dynamic channel analysis, it is convenient to characterize the power tracking capability of the distributed PC algorithms. Fig. 11 represents typical transmitted power profiles for an arbitrary user when optimum (centralized), DCPC, MODPC, FMA, and MIDPC algorithms are used. The result of CSOPC algorithm has been omitted to enhance the visibility of the graphs because it contains high overshoots (the transmitted power falls close to zero at iterations 4,5, and 8).Again, the MIDPC algorithm outperforms the other algorithms in tracking the optimum profile and reacts faster to its variations.

As final step in the performance evaluation of the proposed MITDPC algorithm in this paper, we consider the error incurred in the TPC command. Fig. 12 shows the error norm power and the outage percentage for different levels of error probabilities (%0, %5, and 15%) in the TPC. It is seen that the proposed MITDPC algorithm has a near ideal convergence behavior even with 1-bit feedback TPC command.

6. Conclusion

A new distributed PC algorithm based on optimization techniques was presented in this work. The three simultaneously optimized objectives were determined so as to reduce the SINR fluctuations as well as maintaining the SINR to an acceptable level and minimizing the average transmitted power. Based on snapshot analysis, it was proven that, starting from any initial power vector, the power vector sequence generated by the proposed algorithm converged to a fixed point. Simulation results also showed that, compared to other most known algorithms in the field of PC, our algorithm achieved a better performance in terms of both convergence speed and average transmitted power. Even with using a 1-bit TPC command, the practical version of our algorithm still converged to a fixed point with superior performance compared to the FSPC and the MOTDPC algorithms. Finally, the MITDPC algorithm converged to a fixed point even with error in the TPC command.

References

[1] J. Zander, "Performance of optimum transmitter power control in cellular radio systems," *IEEE Transactions on Vehicular Technology,* vol. 41, no. 1, pp. 57-62, 1992.

[2] J. Zander, "Distributed co-channel interference control in cellular radio systems," *IEEE Transactions on Vehicular Technology,* vol. 41, no. 3, pp. 305-311, 1992.

[3] S. A. Grandhi, R. Vijayan, D. J. Goodman, and J. Zander, "Centralized power control in cellular radio systems," *IEEE Trans. Veh. Technol.,* vol. 42, pp. 466–468, Nov. 1993.

[4] S. A. Grandhi, R. Vijayan, D. J. Goodman, "Distributed power control in cellular radio systems," *IEEE Transactions on Vehicular Technology,* vol. 42, no. 2/3/4, pp. 226-228, 1994.

[5] G. J. Foschini, Z. Milijanic, "A simple distributed autonomous power control algorithm and its convergence," *IEEE Trans. Veh. Technol.,* vol. 42, no. 4, pp. 641–646, 1993.

[6] D. Mitra, "An asynchronous distributed algorithm for power control in cellular radio systems," In Proc. Fifth WINLAB Workshop on Third Generation Wireless Information Networks, pages 249-259, 1993.

[7] S. Grandhi and J. Zander, "Constrained power control in cellular radio systems," *in Proc. IEEE Vehicular Technology Conf., 1994,* vol. 2, pp. 824–828.

[8] R. Yates, "A framework for uplink power control in cellular radio systems," *IEEE J. Select. Areas in Comm.,* vol. 13, pp. 1341-1347, Sept. 1995.

[9] C. Y. Huang and R. D. Yates, "Rate of convergence for minimum power assignment in cellular radio systems," *ACM/Baltzer Wireless Networks Journal,* vol. 4, pp. 223–231, Apr. 1998.

[10] R. Jäntti and S. Kim, "Second-order power control with asymptotically fast convergence," *IEEE J. Sel. Areas Comm.,* vol. 18, no. 3, pp. 447–457, Mar. 2000.

[11] Z. Uykan, R. Jäntti, and H. N. Koivo, "A PI-power control algorithm for cellular radio systems," in *Proc. IEEE-ISSSTA,* vol. 2, pp. 782–785, Sept. 2000.

[12] Z. Uykan and H. N. Koivo, "Sigmoid basis nonlinear power control algorithm for mobile radio systems," *IEEE Trans. Veh. Technol.,* vol. 53, no. 1, pp. 265–271, Jan. 2004.

[13] Z. Uykan and H. N. Koivo, "Proportional power control algorithm for time varying link gains in cellular radio systems," *IEEE Trans. Veh. Technol.,* vol. 55, no. 1, pp. 341–349, Jan. 2006.

[14] Z. Uykan and H. N. Koivo, "Variable structure power control algorithm in mobile radio systems," *IEEE Trans. Wireless Communication.,* vol. 5, no. 10, pp. 2633–2637, Oct. 2006.

[15] L. Qian and Z. Gajic, "Variance minimization stochastic power control in CDMA systems," *IEEE Transactions on Wireless Communications,* vol. 5, no. 1, pp. 193–202, January 2006.

[16] S. Jagannathan, M. Zawodniok, and Q. Shang, "Distributed power control for cellular networks in the presence of channel uncertainties," *IEEE Transactions on Wireless Communications,* vol. 5, no. 3, 540–549, March 2006.

[17] M. S. Elmusrati and H. Koivo, "Multi-objective distributed power control algorithm," in *Proc. IEEE Veh. Tech. Conf. (VTC),* vol. 2, pp. 812–816, Sept. 2002.

[18] M. Elmusrati, H. El-Sallabi, H. Koivo, "Applications of Multi-Objective Optimization Techniques in Radio Resource Scheduling of Cellular Communication Systems," *IEEE Transactions on Wireless Communications,* vol. 7, no. 1,pp. 779–788, Jan. 2008.

[19] H. Farrokhi, M. Rezayi, "An Improved Distributed Power-Control Scheme for Cellular Mobile Systems*", Turkish Journal of Electrical Engineering & Computer Sciences,* vol.20, No.1, pp. 1,8, 2012.

[20] K. Miettinen, *Nonlinear multiobjective optimization*, Boston: Kluwer Academic Publishers, 1998.

[21] C. Coello, "A short tutorial on evolutionary multiobjective optimization," *First Int. Conf. on Evolutionary Multi-Criterion Optimization, Springer-Verlag,* Mar. 2001, pp. 21-40.

[22] J. Candy, *Signal Processing- the modern approach*, McGraw-Hill, 1987.

[23] M. Elmusrati, M. Rintamäki, I. Hartimo and H. Koivo, "Fully distributed power control algorithm with one bit signaling and nonlinear error estimation," in *Proc. IEEE Vehicular Technology Conf.,* Orlando, USA, Oct. 2003.

[24] F. Berggren and R. Jäntti, "Asymptotically fair transmission scheduling over fading channels," *IEEE Trans. Wireless Commun.,* vol. 3, no. 1,pp. 326–336, Jan. 2004.

[25] A. J. Viterbi, *CDMA: Principles of Spread Spectrum Communication*, Addison-Wesley Pub. Co., 1995.

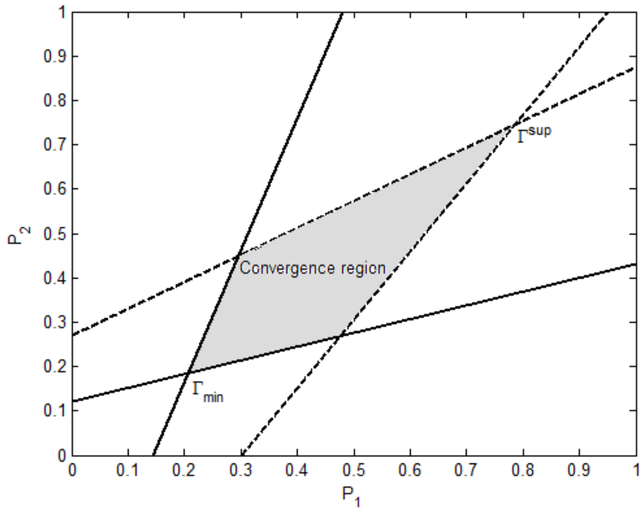

Fig. 1 Convergence region of MIDPC algorithm

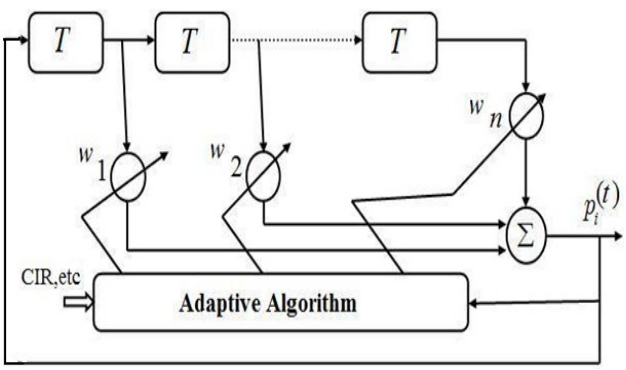

Fig. 2 Autoregressive model of PC

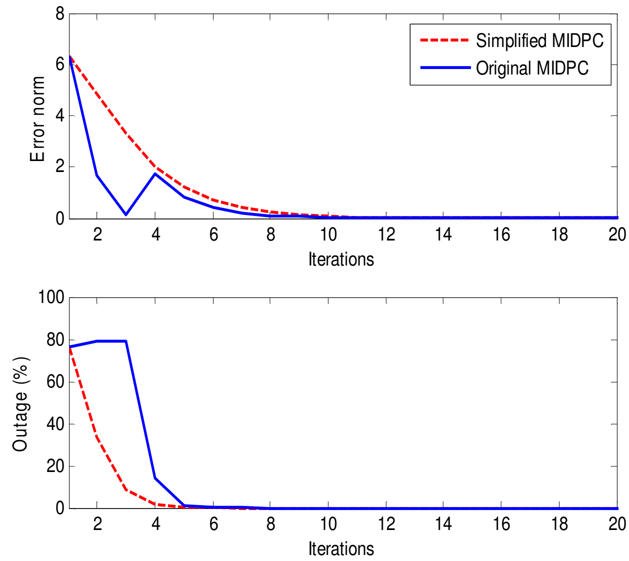

Fig. 3 Effect of simplifications on the MIDPC algorithm

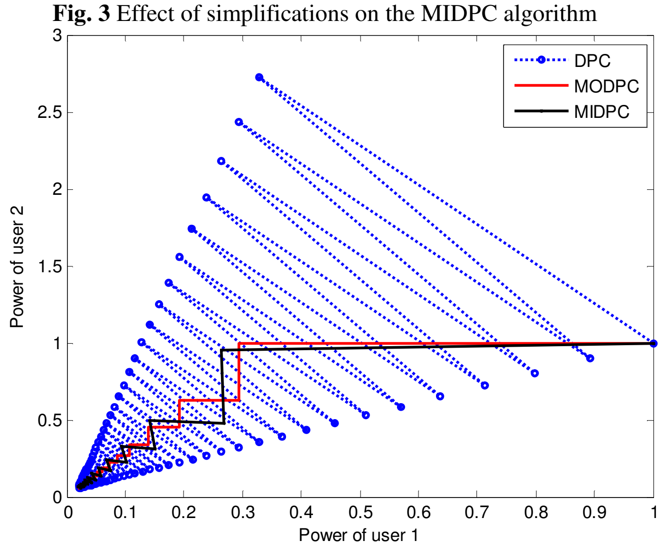

Fig. 4 Power convergence path trajectories for a 2-user system for different distributed algorithms

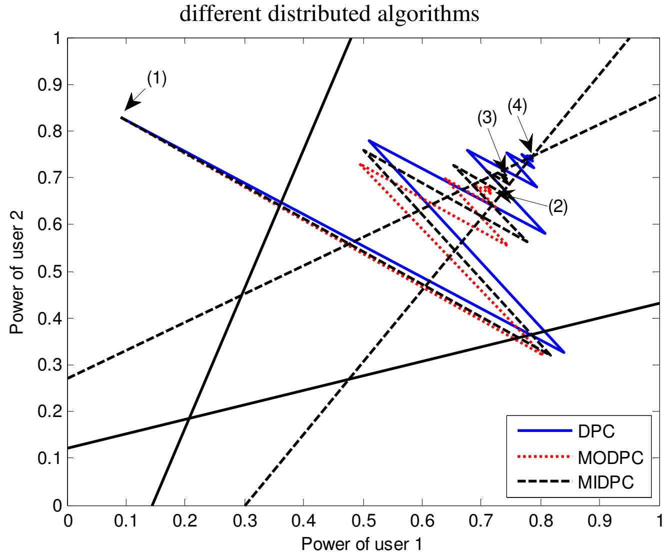

Fig. 5 Distinction of power convergence points for various distributed algorithms

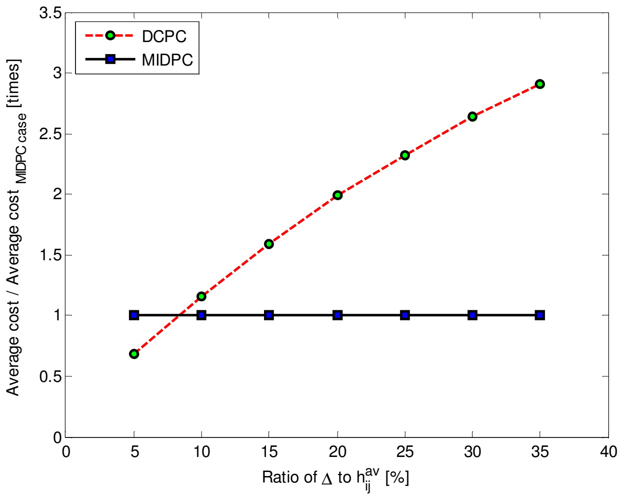

Fig. 6 Average $\left\|\Gamma(t)-\Gamma^{\sup}\right\|_2$ / Average $\left\|\Gamma(t)-\Gamma^{\sup}\right\|_{\text{MIDPC case}}$ with vs. Δ_t / h_{ij}^{av}

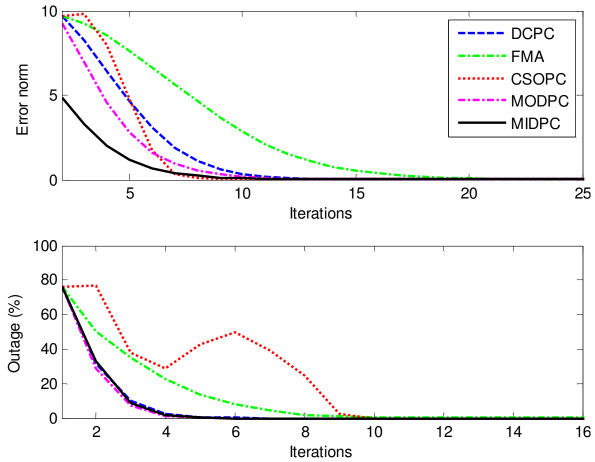

Fig. 7 Error norm and outage percentage for various distributed algorithms in static scenario

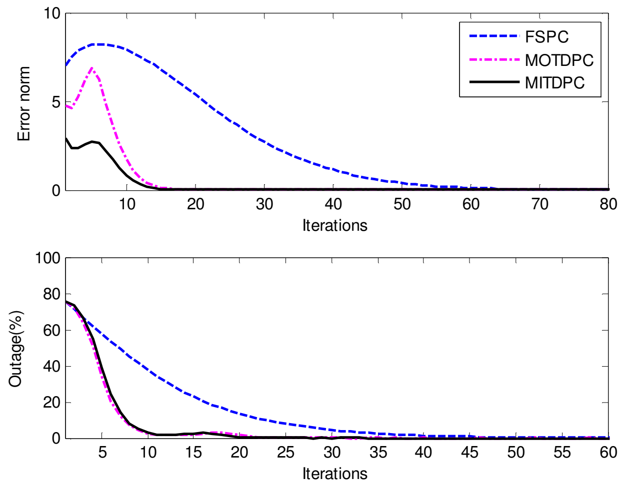

Fig. 8 Error norm and outage percentage for various totally distributed algorithms in static scenario

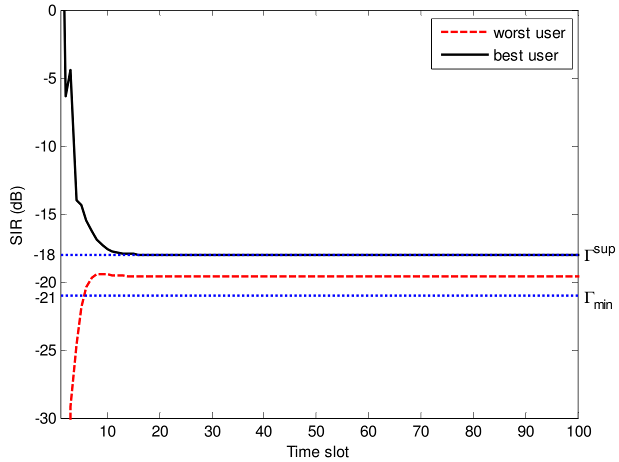

Fig. 9 Received SINR (dB) for best and worst users

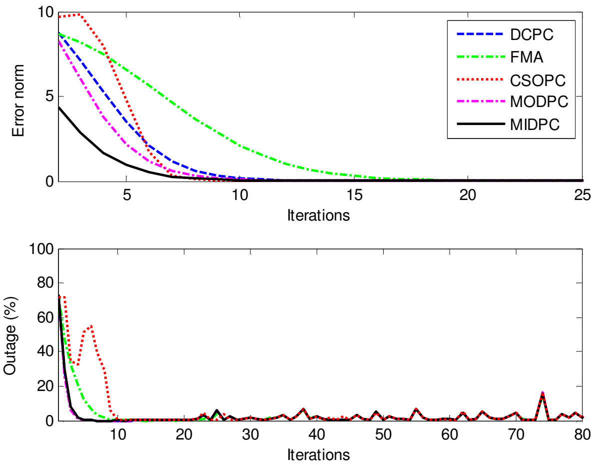

Fig. 10 Error norm and outage percentage for various distributed algorithms in dynamic scenario

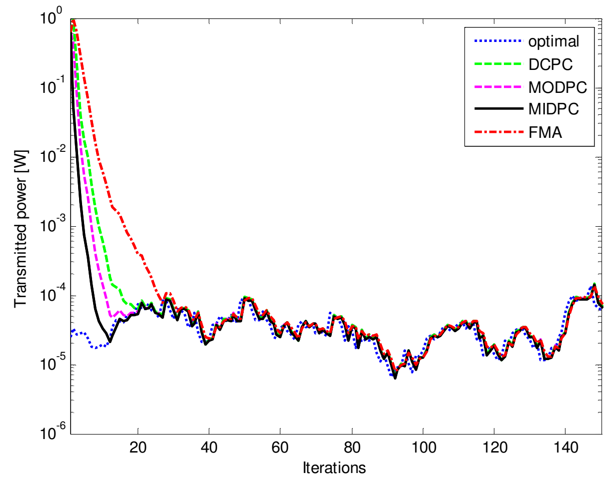

Fig. 11 User's transmitted power for various distributed algorithms

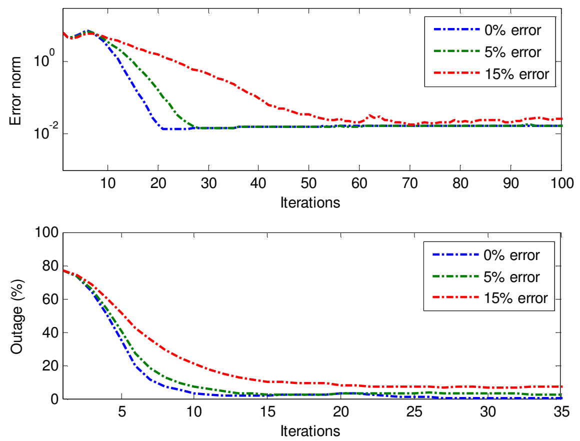

Fig. 12 Convergence behavior of MITDPC algorithm in terms of error norm and outage percentage for gifferent error levels in TPC command

Table1 Average transmitted power (dBW) comparisons for arious distributed PC algorithms

PC Algorithm	DCPC	FMA	CSOPC	MODPC	MIDPC	FSPC	MOTDPC	MITDPC
Static Scenario	-17.27	-15.00	-17.55	-18.07	-20.04	-9.97	-15.86	-18.35
Dynamic Scenario	-14.09	-12.67	-15.48	-15.81	-17.97	-8.16	-13.84	-16.43