

Adaptive Resource Allocation Algorithm in Wireless Access Network

Zhanjun Liu, Yue Shen*, Zhonghua Yu, Fengxie Qin, Qianbin Chen

Chongqing Key Laboratory of Mobile Communication Technology,
Chongqing University of Posts and Telecommunications (CQUPT), Chongqing, 400065, China

*Corresponding author, e-mail: kimjjpcy@163.com

Abstract

Wireless network state varies with the surrounding environment, however, the existing resource allocation algorithm cannot adapt to the varying network state, which results to the underutilization of frequency and power resource. Therefore, in this paper, we propose an adaptive resource allocation algorithm which can efficiently adapt to the varying network state by building an optimal mathematical model and then changing the weighted value of the objective function. Furthermore, the optimal allocation of subcarrier and power is derived by using the Lagrange dual decomposition and the subgradient method. Simulation results show that the proposed algorithm can adaptively allocate the resource to the users according to the varying user density which represents the network state.

Keywords: wireless access network, network environment, adaptive, resource allocation, lagrange dual

Copyright © 2016 Universitas Ahmad Dahlan. All rights reserved.

1. Introduction

With the development of wireless mobile communication such as 4G and 5G, the number of mobile terminal is increasing growing, and the fluctuation of user density also becomes higher, e.g., the user density of commercial areas in daytime is higher than that in evening, and the user density of residential areas in daytime is lower than that in evening. Consequently, the changing user density will affect the wireless network state. In addition, the inherent characteristic of wireless network is that the users are always in movement. Therefore, an effective adaptive resource allocation is necessary for the varying network [1].

Existing resource allocation algorithms can be divided into two categories based on the optimization criteria. One is to take the users' throughput maximization as the objective function [2, 3], and the other is to take the base station's (BS's) power minimization as the objective function [4, 5]. In [2], the resource allocation mechanism with a two-step suboptimal algorithm is proposed, which jointly allocates subcarrier and power to maximize the minimum rate of all users while improving the system throughput. In [3], a adaptive resource allocation based on OFDMA fish swarm algorithm are studied to maximize the system throughput. The proposed mechanism includes subcarrier allocation based on a new way and power allocation based on the improved adaptive fish algorithm. The authors in [4] propose the resource allocation algorithm includes three steps. Firstly, initialize the subcarriers allocation according to channel gain, then, select the most suitable subcarrier for users by comparing the power. Finally, assign bits for subcarriers by utilizing the greedy water-filling algorithm. In [5], the authors use Hungarian algorithm to initially perform the subcarrier allocation, and then dynamically allocates bit to subcarriers based on the channel state information (CSI), finally adjust the power of subcarriers to minimize the transmission power.

Even though the above algorithms can improve the system performance under certain situations, however, once the resource allocation optimization models are built, their objective function is constant no matter how the wireless network state changes. i.e, they are all fixed resource allocation algorithm. However, the users' movement will lead to the variation of network environment, and the fixed resource allocation is not optimal for the changing wireless network. In the case of high user density, the resource scarcity is the major problem, and the target of resource allocation is to maximize the network capacity. However, in the case of low user density, the target becomes to guarantee the quality of service (QoS) and reduce the total

BS's power consumption according to the Shannon Theory. As the existing resource allocation algorithm cannot dynamically vary with the varying wireless network state/user density. Therefore, in this paper, an adaptive resource allocation algorithm is proposed, which not only can adjust itself to the varying network environment, but also can achieve the self-optimization. The proposed algorithm firstly builds a mathematical model by combining with the varying characteristics of user density, and then the optimal allocation of subcarriers and power is performed by using the Lagrange dual decomposition. Furthermore, in order to reduce the computation complexity, we decompose the original problem into several independent sub-problems. Simulation results show that the proposed algorithm can adaptively allocate the resource to the users according to the varying user density which represents to the wireless network state.

2. System Model and Problem Formulation

We consider a single-cell scenario for the multiuser cellular network with a BS [6]. We assume that the total number of subcarriers is N , the total transmit power of BS is P_{total} , the minimum requirement and maximum limit of user rate is R_{min} and R_{max} , respectively. K users are uniformly distributed over the cell, and $h_{k,n}$ is the channel gain of subcarrier n between BS and user k . Moreover, the BS is assumed to be able to obtain the CSI feedback [7], which follows the frequency selective fading [8].

The transmission rate of user k on subcarrier n is $R_{k,n}$, and it can be represented as [9]:

$$R_{k,n} = B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) \quad (1)$$

Where B and σ^2 are subcarrier bandwidth and additive white Gaussian noise power, respectively.

The throughput of each user is represented as:

$$R_k = \sum_{n=1}^N \rho_{k,n} B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) \quad (2)$$

Where $\rho_{k,n} = 1$ denotes that subcarrier n is utilized by user k , or else $\rho_{k,n} = 0$.

The total power consumption is:

$$P = \sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} P_{k,n} \quad (3)$$

As described earlier, when user density is high, the main objective of resource allocation is to maximize the users' throughput, i.e.:

$$\max \sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) \quad (4)$$

When user density is low, the main objective becomes to minimize the BS's power consumption, i.e.:

$$\min \sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} P_{k,n} \quad (5)$$

Hence, we can formulate the above multiple objective optimization function as a single-objective optimization function:

$$\max \alpha \sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) - (1-\alpha) \sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} P_{k,n} \quad (6)$$

$$s.t. \sum_{n=1}^N \rho_{k,n} B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) \geq R_{\min} \quad (7)$$

$$\sum_{n=1}^N \rho_{k,n} B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) \leq R_{\max} \quad (8)$$

$$\sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} P_{k,n} \leq P_{total} \quad (9)$$

$$\rho_{k,n} \in \{0,1\} \quad (10)$$

$$\sum_{k=1}^K \rho_{k,n} = 1 \quad (11)$$

Where α varies with the number of users K , and it describes the importance of network performance when the user's density is in variation.

Equation (7) represents the minimum requirement of each user's rate, (8) represents the maximum rate limit of each user, (9) represents the total transmitted power limit of the BS, (10) and (11) represent that a subcarrier cannot be occupied by more than one user at the same time.

3. Adaptive Resource Allocation Algorithm Based on Dual Decomposition

If an optimization problem satisfies the characteristics of the time-sharing, and then the original problem and its dual problem have a zero duality gap [10]. Therefore, the original problem and the dual problem have the same optimal solution. Equation (6) is a non-convex problem. If the number of subcarrier is large enough, the optimization problem obviously satisfies the time-sharing condition, therefore, we can take advantage of the Lagrange dual decomposition method to solve the optimization problem where the solution is progressive optimal [11].

Therefore, in this section, the solution of Equation (6) is derived by using Lagrange dual decomposition method. Let λ , β and μ be Lagrange multipliers, respectively. Therefore, the Lagrange dual function of (6) can be expressed as:

$$\begin{aligned} g(\lambda, \beta, \mu) &= \max L(\rho, P, \lambda, \beta, \mu) \\ &= \max \left\{ \sum_{k=1}^K \sum_{n=1}^N [\alpha \rho_{k,n} B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) - (1-\alpha) \sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} P_{k,n}] \right. \\ &\quad + \sum_{k=1}^K \lambda_k \left(\sum_{n=1}^N \rho_{k,n} B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) - R_{\min} \right) \\ &\quad \left. + \sum_{k=1}^K \beta_k \left(R_{\max} - \sum_{n=1}^N \rho_{k,n} B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) \right) + u \left(P_{total} - \sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} P_{k,n} \right) \right\} \\ &= \max \left\{ \sum_{k=1}^K \sum_{n=1}^N \rho_{k,n} [\alpha B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) - (1-\alpha) P_{k,n} - \beta_k B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) \right. \\ &\quad \left. + \lambda_k B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) - \mu P_{k,n}] - \sum_{k=1}^K \lambda_k R_{\min} + \sum_{k=1}^K \beta_k R_{\max} + \mu P_{total} \right\} \end{aligned} \quad (12)$$

$$\text{Where: } \boldsymbol{\rho} = \begin{bmatrix} \rho_{1,1} & \rho_{1,2} & \dots & \rho_{1,n} \\ \dots & \dots & \dots & \dots \\ \rho_{k,1} & \rho_{k,1} & \dots & \rho_{k,n} \end{bmatrix}, \mathbf{P} = \begin{bmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,n} \\ \dots & \dots & \dots & \dots \\ P_{k,1} & P_{k,2} & \dots & P_{k,n} \end{bmatrix}$$

Optimization problem of dual domain can be represented as:

$$\min_{\lambda \geq 0, \beta \geq 0, \mu \geq 0} g(\boldsymbol{\lambda}, \boldsymbol{\beta}, \mu) \quad (13)$$

As the dual domain problem $g(\boldsymbol{\lambda}, \boldsymbol{\beta}, \mu)$ is linear for $\boldsymbol{\lambda}$, $\boldsymbol{\beta}$ and μ , therefore, it becomes a convex optimization problem, and then we can use subgradient iteration method to guarantee that the $g(\boldsymbol{\lambda}, \boldsymbol{\beta}, \mu)$ can converge to minimum value. Moreover, the Lagrange multipliers are updated based on the following Equations [12]:

$$\lambda_k^{i+1} = \lambda_k^i - y_k^i \left[\sum_{n=1}^N \rho_{k,n}^* B \log_2 \left(1 + \frac{P_{k,n}^* |h_{k,n}|^2}{\sigma^2} \right) - R_{\min} \right] \quad (14)$$

$$\mu^{i+1} = \mu^i - z^i (P_{\text{total}} - \sum_{n=1}^N \rho_{k,n}^* P_{k,n}^*) \quad (15)$$

$$\beta_k^{i+1} = \beta_k^i - \varpi_k^i \left[R_{\max} - \sum_{n=1}^N \rho_{k,n}^* B \log_2 \left(1 + \frac{P_{k,n}^* |h_{k,n}|^2}{\sigma^2} \right) \right] \quad (16)$$

Where $\rho_{k,n}^*$ and $P_{k,n}^*$ are the optimal subcarrier and power allocation which can satisfy equation (6), respectively. The number of iterations is i . y_k^i , ϖ_k^i and z^i are the iteration step length of Lagrange multipliers, respectively.

$$\lim_{i \rightarrow \infty} y_k^i = 0, \sum_{i=1}^{\infty} y_k^i = \infty; \lim_{i \rightarrow \infty} z^i = 0, \sum_{i=1}^{\infty} z^i = \infty; \lim_{i \rightarrow \infty} \varpi_k^i = 0, \sum_{i=1}^{\infty} \varpi_k^i = \infty \quad (17)$$

If the step length satisfies the criteria in (17), the subgradient method can converge to the optimal dual solution.

The optimization variables $\boldsymbol{\rho}$ and \mathbf{P} need to be determined under the case of given dual variables $\boldsymbol{\lambda}$, $\boldsymbol{\beta}$ and μ for the solution of the dual function $g(\boldsymbol{\lambda}, \boldsymbol{\beta}, \mu)$. In order to reduce the computation complexity, the dual problem is decomposed into N independent optimization problem.

$$g(\boldsymbol{\lambda}, \boldsymbol{\beta}, \mu) = \sum_{n=1}^N g_n(\boldsymbol{\lambda}, \boldsymbol{\beta}, \mu) - \sum_{k=1}^K \lambda_k R_{\min} + \sum_{k=1}^K \beta_k R_{\max} + \mu P_{\text{total}} \quad (18)$$

$$g_n(\boldsymbol{\lambda}, \mu) = \max \left[\sum_{k=1}^K \rho_{k,n} \alpha B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) - \sum_{k=1}^K \rho_{k,n} (1 - \alpha) P_{k,n} \right. \\ \left. + \sum_{k=1}^K \rho_{k,n} \lambda_k B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) - \sum_{k=1}^K \rho_{k,n} \beta_k B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) - \sum_{k=1}^K \rho_{k,n} \mu P_{k,n} \right] \quad (19)$$

The Equation (19) can be transferred into the below formats by using Karsh-Kuhn-Tucker condition [13].

$$\frac{\partial g_n(\boldsymbol{\lambda}, \mu)}{\partial P_{k,n}} = \frac{\rho_{k,n} B |h_{k,n}|^2 (\alpha + \lambda_k - \beta_k)}{\ln(2)(\sigma^2 + P_{k,n} |h_{k,n}|^2)} - \rho_{k,n} (1 - \alpha + \mu) \quad \forall k, n \quad (20)$$

$$\frac{\partial g_n(\boldsymbol{\lambda}, \mu)}{\partial \rho_{k,n}} = B \log_2 \left(1 + \frac{P_{k,n} |h_{k,n}|^2}{\sigma^2} \right) (\alpha + \lambda_k - \beta_k) - P_{k,n} (1 - \alpha + \mu) \quad \forall k, n \quad (21)$$

The optimal power allocation can be obtained under the conditions of the specific subcarrier allocation by using of KKT condition:

$$P_{k,n} = \left[\frac{B(\alpha + \lambda_k - \beta_k)}{\ln(2)(1 - \alpha + \mu)} - \frac{\sigma^2}{|h_{k,n}|^2} \right]^+ \quad \forall k, n \quad (22)$$

Where $[A]^+$ represent $\max(0, A)$, and (23) is derived by substituting (22) to (19):

$$g_n(\boldsymbol{\lambda}, \mu) = \max_{1 \leq k \leq K} (\alpha + \lambda_k - \beta_k) B \left[\log_2 \left(\frac{B |h_{k,n}|^2 (\alpha + \lambda_k - \beta_k)}{\sigma^2 \ln(2)(1 - \alpha + \mu)} \right) \right]^+ - (1 - \alpha + \mu) \left[\frac{B(\alpha + \lambda_k - \beta_k)}{\ln(2)(1 - \alpha + \mu)} - \frac{\sigma^2}{|h_{k,n}|^2} \right]^+ \quad \forall k \quad (23)$$

From the above analyses, we can get the optimal allocation rule of subcarrier:

$$k^* = \arg \max_k \left\{ (\alpha + \lambda_k - \beta_k) B \left[\log_2 \left(\frac{B |h_{k,n}|^2 (\alpha + \lambda_k - \beta_k)}{\sigma^2 \ln(2)(1 - \alpha + \mu)} \right) \right]^+ - (1 - \alpha + \mu) \left[\frac{B(\alpha + \lambda_k - \beta_k)}{\ln(2)(1 - \alpha + \mu)} - \frac{\sigma^2}{|h_{k,n}|^2} \right]^+ \right\}$$

$$\rho_{k^*,n} = 1 \quad (24)$$

The optimal power allocation rules: the BS allocates power on the corresponding subcarrier of users by following equation (22), when the allocation of subcarrier is already finished.

We finally obtain the optimal allocation rules of subcarrier and power by deriving Equation (6), which can adapt to the user density. The allocation rules of the proposed algorithm are summarized as:

Step 1: Initialize $y_k^0, z^0, \varpi_k^0, \lambda_k^0, \mu^0, \beta_k^0, \forall k, n$ with random non-negative numbers.

Step 2: Obtain optimal subcarrier allocation by using the current Lagrange multiplier according to equation (24).

Step 3: Obtain optimal power allocation on each subcarrier according to equation (22).

Step 4: Update Lagrange multiplier according to equations (14), (15) and (16).

Step 5: Go back to step2 until convergence.

4. Simulation Analysis

In this section, we describe the simulation parameters and performance of the proposed algorithm. The simulation parameters are shown in Table 1. Figure 1 is the capacity comparison among algorithm 1, algorithm 2 and the proposed algorithm, wherein algorithm 1 only takes the maximization of system throughput as the objective function [14], and algorithm 2 only considers the minimization of BS's power consumption as the objective function [15]. From the Figure 1, we can observe that the curve of throughput approaches to algorithm 2 when the user density is low, because in this case, the wireless resource is very sufficient, and the main target of resource allocation is to minimize the BS's power consumption which is able to satisfy the user rate requirement according to the Shannon theory, i.e., Channel capacity is not only dependent on the bandwidth, but also the transmission power. However, with the increase of the number of users, the wireless resource becomes shortage, and the main target becomes to maximize the system throughput, that is to say, in order to satisfy the user rate requirement, it's

cannot take the minimization of BS's power consumption as the objective function again, and consequently, the curve approaches to algorithm 1.

Figure 2 is the BS's power consumption of algorithm 1, algorithm 2 and the proposed algorithm. From Figure 2, we can see that when the number of users is low, the objective of resource allocation is to satisfy the minimum rate requirement of each user and minimize the BS's power consumption, whereas the maximization of system throughput is not the main factor which we should consider. Therefore, the curve of power consumption approaches to algorithm 2, which achieves the optimization of power consumption. With the increase of user density, the resource shortage becomes serious, and then the maximization of system throughput becomes the main objective, which leads to more power consumption to satisfy the rate requirement based on the Shannon theory. Therefore, the curve of power consumption approaches to algorithm 1, which increase the power consumption. In conclusion, the proposed algorithm can be adaptive to the varying of user density as well as the changing network environment.

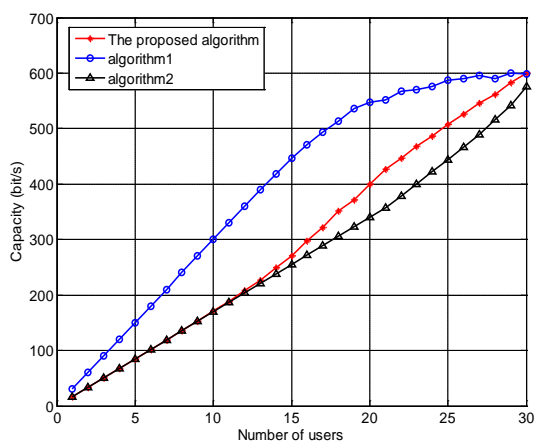


Figure 1. Number of Users vs. Capacity

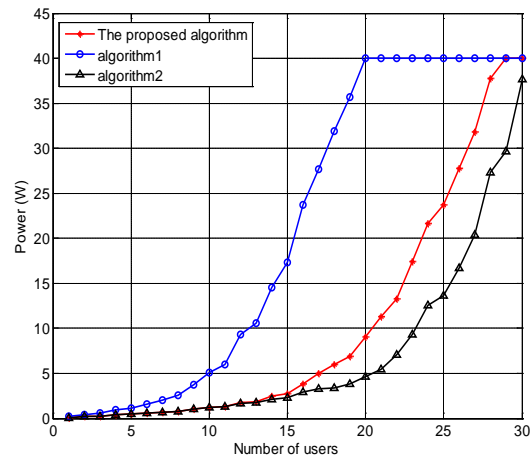


Figure 2. Number of Users vs. Power

Table 1. Simulation Parameters

Parameters	Values
System Bandwidth	2 MHz
Number of subcarriers	64
User's lowest rate	17 bit/s
User's maximal rate	30 bit/s
Total power	46 dbm
White Gaussian noise power	10^{-2} W
Channel model	Rayleigh fading channel
Number of users K	1~30
α	K/30

5. Conclusion

As the traditional resource allocation cannot adaptively vary with the wireless communication environment. Therefore, in this paper, we propose an adaptive resource allocation algorithm to adapt to the dynamic network environment. Firstly, an optimization mathematical model is built according to the varying network environment. Then, the weights of objective function dynamically vary with this kind of variation, which leads to the adaptation. Furthermore, the Lagrange dual method and subgradient method is utilized to get the optimal solution of the optimization model. Finally, in order to verify the algorithm performance, we assume that user density is utilized to represent the varying network environment, and the total wireless resource is fixed. The resource shortage is the most challenges at present when the user density is higher, so the target of resource allocation becomes to maximize the system throughput. However, the resource is sufficient when the user density is lower, and the target of

resource allocation becomes to satisfy the QoS request of each user and lower the power consumption. Simulation results show that, in the case of varying user density, we can obtain the adaptive resource allocation by changing the weights of objective function, and it's also verify the validity of the proposed algorithm. We believe that our proposed algorithm is promising for the future 5G mobile communication system.

Acknowledgements

This work is supported by 863 project (2014AA01A701) and the Science and Technology Research Project of Chongqing Municipal Education Commission of China (KJ120510).

References

- [1] Liu Jiayong. Research on Adaptive Resource Allocation Problem in OFDM System. University of Electronic Science and Technology of China. 2008.
- [2] Zhang Xiaoxia, Xuemin Sherman Shen, Xie Liangliang. Joint Subcarrier and Power Allocation for Cooperative Communications in LTE-Advanced Networks. *IEEE Transactions on Wireless Communications*. 2014; 13(2): 658-668.
- [3] Wang Zhao, Li Youming, Chen Bin. OFDMA Adaptive Resource Allocation Based on Fish Swarm Algorithm. *Acta Physica Sinica*. 2013; 62(12): 1-7.
- [4] Cao Shaolong, Zhou Li, Li Bin. Resource Allocation Algorithm for MIMO-OFDM System Based on Minimum Transmitting Power. *Computer Systems & Applications*. 2014; 23(5): 192-195.
- [5] Tian Yilan, Xu Boqing. Subcarrier and Bit Allocation Algorithm for Multi-user OFDM System. *Radio Communications Technology*. 2012; 9(4): 35-37.
- [6] Tan Zhenglin, Deng Xiaocheng. Resource Allocation Algorithm for Single Cell Downlink of Multiuser OFDM System. *Information Technology*. 2012; 8(7): 92-95.
- [7] Jang J, Lee KB. Transmit Power Adaptation for Multiuser OFDM Systems. *IEEE Journal on Selected Areas Communications*. 2003; 21(2): 171-178.
- [8] KM Awan, AH Abdullah, K Hussain. Additional Resource Allocation for Improving Fairness in WiMAX. *TELKOMNIKA Telecommunication, Computing, Electronics and Control*. 2014; 12(2): 455-464.
- [9] NM Adriansyah, M Asvial, B Budiardjo. Modified Greedy Physical Link Scheduling Algorithm for Improving Wireless Mesh Network Performance. *Telkomnika Telecommunication, Computing, Electronics and Control*. 2015; 13(1): 202-210.
- [10] Yu W, Liu R. Dual Methods for Nonconvex Spectrum Optimization of Multicarrier Systems. *IEEE Transaction on Communications*. 2006; 54(7): 1310-1322.
- [11] Zhang Cuizhi, Chen Shumin, Yu Qiang, Liang Shucheng, Xu Yuanxin. Power Allocation and Subcarrier Pairing for AF-OFDM Based Cognitive Radio Systems. *Journal of Zhejiang University (Engineering Science)*. 2011; 62(12): 2259-2264.
- [12] Boyd S, Xiao L, Mutapcic A. Subgradient Methods [EB/OL]. 2003.
- [13] Boyd S, Vandenberghe L. *Convex Optimal*. Cambridge, UK: Cambridge University Press. 2004: 215-247.
- [14] Ding Bin. The Sub-optimal Power Allocation Adaptive Algorithm in OFDM Technology. *Computer Knowledge and Technology*. 2015; 20(12): 223-224.
- [15] Fu Chunsheng, Fu Bilin, Chen Ler, She Feng. Power Minimization Algorithm for Multi-user MIMO-OFDM System. *Video Engineering*. 2009; 33(S1): 119-121.