Quality-of-Service Driven Resource Allocation via Stochastic Optimization for Wireless Multi-user Relay Networks

Xiao Yin[1,2], Yanbo Ma[1(✉)], Qiang Liu[1], and Wei Su[1]

[1] Shandong University of Finance and Economics, Jinan, China
{yanboma,qiangliu,suwei}@sdufe.edu.cn
[2] Shandong Provincial Key Laboratory of Software Engineering, Jinan, China
yx_018@126.com

Abstract. This paper presents a power allocation algorithm for optimizing network resources while considering the delay provisioning in multi-user relay networks. Our aim is to minimize the average power consumed by the relay nodes while satisfying the minimum Qos requirement of all users. Employing the convex optimization theory, we derive an optimal power allocation policy in a quasi-closed form and give two rules of how to select the relay nodes. Furthermore, a stochastic power method is developed to learn the fading state of the channels and carry out the optimal strategy immediately. Moreover, numerical results are provided to demonstrate the performance of the proposed resource allocation policies.

Keywords: Resource allocation · Wireless relay networks · QoS · Effective capacity · Stochastic optimization · Convex optimization

1 Introduction

Nowadays, green communication is a growing research area which strives for designing energy awareness communication systems so as to enhance energy efficiency [1]. Energy awareness in wireless networks can be achieved by using low-power relays for coverage extension, or improving wireless resource/interference management. Among these approaches, relay based cooperative communication requires minimum modification in the existing network infrastructure, and has been one active research area. By exploiting spatial diversity the cooperative communication schemes [2,3] are well recognized as an effective way to improve the network performance (e.g. capacity, power efficiency, reliability) at the physical layer. Motivated by this, in this paper we consider an effective resource allocation scheme to improve the network capacity for wireless multi-user relay networks.

Many energy-efficient resource allocation schemes addressing this topic have been published recently [4–7]. The framework employed in the cited literatures is mainly based on the information theory. However, it is worth to mention that this

Q. Chen et al. (Eds.): ChinaCom 2016, Part I, LNICST 209, pp. 316–325, 2018.
DOI: 10.1007/978-3-319-66625-9_31

framework is not suitable for the delay-sensitive multimedia applications, since Shannon theory places no restriction on the delay of the transmission scheme achieving capacity. In order to supply the multimedia applications, in this paper we consider the QoS metric of the statistical delay, which describes a delay-bound violation probability upper-bounded by a certain given value. And the statistical delay related effective capacity [8] is adopted to describe the network capacity for the multimedia applications. It is worth to mention the effective capacity was first introduced by Wu and Negi to describe the maximal arrival rate which can be supported under guaranteed delay QoS requirements. The concept of effective capacity provides us with a degree of freedom to discuss the queueing behaviors at data link layer, such as queue distribution, buffer overflow probabilities, and delay-bound violation probabilities.

As the extended application of effective capacity for wireless networks, in this paper we utilize the concept of effective capacity and provide a general framework for optimizing network resources while considering the delay provisioning in multi-user relay networks. The proposed policy aims to minimize the average power consumed by the relay nodes while satisfying the rate constraints of all users. With the effective capacity theory, the resource allocation policy is cross-layer based and delay QoS oriented jointly. Employing the convex optimization theory, an optimal power allocation policy is derived in a quasi-closed form and two rules of how to select the relay nodes is derived based on the Karush-Kuhn-Tucker (KKT) conditions. Besides, in order to expand the applied range of the proposed scheme, we takes into account the time-varying nature of fading channels without *a priori* knowledge of the cumulative distribution function (cdf) of the channels. Specifically, we model the channel condition as a stochastic process. Based on the stochastic optimization tools [9–13], the proposed resource allocation schemes can learn the underlying channel distribution. This entails a more systematic and powerful framework for the design and analysis of the stochastic resource allocation schemes in wireless networks.

2 System Model and Problem Formulation

2.1 System Model

Consider a multiuser relay network, where M source nodes (S_j, $j = 1, ..., M$) transmit data to their respective destination nodes (D_j, $j = 1, ..., M$). There are N relay nodes (R_i, $i = 1, ..., N$) which are employed to assist transmissions from source to destination nodes. Premise that there is no direct link between the source and the destination nodes and a relay can forward data for several users. Moreover, orthogonal transmissions are supposed among different users for simultaneous communications by using different frequency bands. The available channel bandwidth is equally divided into M orthogonal subchannels whose bandwidth is denoted by B. Each user is allocated to one subchannel.

At the source, frames from upper layers are put into the queue which is assumed to be infinite-length. Then at the physical layer, frames from the queue are divided into bit-streams. The reverse operations are executed at the receiver.

We assume that the fading processes of all users are jointly stationary and ergodic with continuous joint cumulative distribution. Additionally, the wireless links are assumed to experience different fading from one frame to another, but remain invariant within a frame duration T_f.

Let $h_{R_i}^{S_j}$ and $h_{R_i}^{D_j}$ denote the fading channel coefficient for link S_j–R_i and R_i–D_j, respectively. Let P_{S_j} denote the transmit power of S_j and $P_{R_i}^{S_j}$ denote the power transmitted by the relay R_i for assisting the source S_j. Let N_{R_i} and N_{D_j} denote the variance of the additive white Gaussian (AWGN) at R_i and D_j. We assume that transmission for each source-destination pair via relay nodes is carried out in a time multiplexing manner by Amply-and-forward (AF) protocol. Specifically, each frame duration is equally divided into $N+1$ intervals. The source S_j broadcasts its signal to all relays at the first interval, and each relay forwards the signal to the destination D_j per interval in orders. Assuming that maximum-ratio-combining is employed at the destination node D_j, the signal-to-noise ratio (SNR) at D_j can be written as

$$\gamma_j = \sum_{i=1}^{N} \frac{P_{R_i}^{S_j}}{\alpha_{R_i}^{S_j} P_{R_i}^{S_j} + \beta_{R_i}^{S_j}}, \tag{1}$$

where

$$\alpha_{R_i}^{S_j} = \frac{\frac{N_{R_i}}{N+1}}{|h_{R_i}^{S_j}|^2 P_{S_j}}, \beta_{R_i}^{S_j} = \frac{\frac{N_{D_j}}{N+1}\frac{N_{R_i}}{N+1}}{|h_{R_i}^{S_j}|^2 |h_{R_i}^{D_j}|^2 P_{S_j}} + \frac{\frac{N_{D_j}}{N+1}}{|h_{R_i}^{D_j}|^2}. \tag{2}$$

The data rate from source S_j to destination D_j is given as

$$r_j = \frac{1}{N+1} \log(1+\gamma_j). \tag{3}$$

The rate function $r_j(\cdot)$ has been proven to be a concave increasing function of $P_{R_i}^{S_j}$ [14]. This convexity property will help us formulate a convex optimization for the problem under consideration as will be shown in the next subsection.

2.2 Problem Formulation

Considering the delay provisioning for delay-sensitive traffic, effective capacity is introduced to describe the system throughput with delay QoS guarantees. The effective capacity of link S_j–D_j is described as

$$Ec_j = -\frac{1}{\theta} \log(\mathbb{E}\big[e^{-\theta_j T_f B r_j}\big]), \tag{4}$$

where $\mathbb{E}[\cdot]$ is the expectation operator and r_j is the data rate from S_j to D_j. Note that $Ec_j(\cdot)$ is a monotonically decreasing function of θ, which means a small θ corresponds to a loose violation probability requirement, while a large θ matches a strict QoS requirement. Without loss of generality, let T_f and B be equal to 1.

Let $\bar{a}_j$ denote the effective bandwidth of the source traffic flow of the jth user. The QoS requirements of link S_j–D_j can be guaranteed when $Ec_j \geq \bar{a}_j$ holds, which means that for each source-destination pair, the effective capacity with its required delay QoS exponent is greater or equal to the effective bandwidth of the corresponding source traffic flow. With this delay QoS provisioning, our optimization criteria aims at minimizing the average power consumed by all the relay nodes. Mathematically, we formulate the resource allocation problem considering QoS provisioning as

$$\min_{P_{R_i}^{S_j} \geq 0} \sum_{i=1}^{N} \mathbb{E}_h \left[\sum_{j=1}^{M} P_{R_i}^{S_j} \right] \quad \text{s.t.} \quad Ec_j \geq \overline{a}_j, \forall j, \tag{5}$$

where $\mathbb{E}_h[\cdot]$ denotes the expectation over all fading realizations. Because $log(\cdot)$ is a monotonically increasing function, the constraints of (5) are equivalent to

$$\mathbb{E}_h \left[e^{-\theta_j r_j} \right] - e^{-\theta_j \overline{a}_j} \leq 0, \forall j. \tag{6}$$

The objective function of (5) is linear. The constraints (6) are convex since $r_j(\cdot)$ is convex. Therefore, the formulated power allocation problem is a convex optimization problem. It can also be proved that the problem in (5) satisfies Slaters constraint qualification. Thus the strong duality holds and solving the dual problem is equivalent to solving the primal problem.

3 Power Allocation and Relay Selection Considering QoS Provisioning

3.1 Dual Decomposition Approach

We first introduce $\boldsymbol{\mu} := [\mu_1, \mu_2, ..., \mu_M]^T$ associated with constraints, where $\boldsymbol{\mu} \succeq 0$. The Lagrangian function by relaxing the constraints can be written as

$$L(P_{R_i}^{S_j}, \boldsymbol{\mu}) = \sum_{i=1}^{N} \mathbb{E}_h \left[\sum_{j=1}^{M} P_{R_i}^{S_j} \right] + \sum_{j=1}^{M} \mu_j \left(\mathbb{E}_h [e^{-\theta_j r_j}] - e^{-\theta_j \overline{a}_j} \right), \tag{7}$$

The dual function is expressed as

$$D(\boldsymbol{\mu}) = \min_{P_{R_i}^{S_j} \geq 0} L(P_{R_i}^{S_j}, \boldsymbol{\mu}), \tag{8}$$

and the dual optimization problem reads as

$$\max_{\boldsymbol{\mu}} D(\boldsymbol{\mu}) \quad \text{s.t. } \mu_j \geq 0, \forall j. \tag{9}$$

Since $D(\boldsymbol{\mu})$ is convex and differentiable, the following gradient iteration algorithm can be used to solve the dual problem (9)

$$\mu_j[t+1] = \left[\mu_j[t] + s \cdot \left(\mathbb{E}_h \left[e^{-\theta_j r_j} \right] - e^{-\theta_j \overline{a}_j} \right) \right]^+, \tag{10}$$

where t is the iteration index, s is a sufficiently small positive step size, and $[x]^+ = \max(0, x)$. The dual variables $\mu_j[t]$ will converge to the optimal μ_j^* as $t \to \infty$, and $P_{R_i}^{S_j}(\mu_j)$ will also converge to the optimal $P_{R_i}^{S_j*}(\mu_j^*)$ owing to the strong duality.

3.2 Power Allocation and Relay Selection Policy with Given $\boldsymbol{\mu}$

Here we will derive the optimal power allocation and relay selection policy with given $\boldsymbol{\mu}$. To find the optimal $P_{R_i}^{S_j}$ that minimizes $L(P_{R_i}^{S_j}, \boldsymbol{\mu})$, we need to solve

$$\min_{P_{R_i}^{S_j} \geq 0} \sum_{j=1}^{M} \mathbb{E}_h \left[\sum_{i=1}^{N} P_{R_i}^{S_j} + \mu_j e^{-\theta_j r_j} \right], \tag{11}$$

which is equivalent to solving the following problem

$$\min \left[\sum_{i=1}^{N} P_{R_i}^{S_j} + \mu_j e^{-\theta_j r_j} \right] \quad \text{s.t.} \quad P_{R_i}^{S_j} \geq 0, \forall i. \tag{12}$$

Clearly, (12) is a convex optimization problem. Let $\boldsymbol{\lambda} := \lambda_i \geq 0 (i = 1, ..., N)$ be the Lagrange multipliers for the constraints $P_{R_i}^{S_j} \geq 0$. The Lagrangian of (12) is

$$\pounds(P_{R_i}^{S_j}, \boldsymbol{\lambda}) = \sum_{i=1}^{N} P_{R_i}^{S_j} + \mu_j e^{-\theta_j r_j} - \sum_{i=1}^{N} \lambda_i P_{R_i}^{S_j}. \tag{13}$$

Define

$$f(P_{R_i}^{S_j}) = \sum_{i=1}^{N} P_{R_i}^{S_j} + \mu_j e^{-\theta_j r_j}. \tag{14}$$

The Karush-Kuhn-Tucker (KKT) conditions for optimization problem (13) are shown as

$$\begin{aligned} \lambda_i^* &\geqslant 0, \forall i, \\ \lambda_i^* P_{R_i}^{S_j *} &= 0, \forall i, \\ f'(P_{R_i}^{S_j *}) - \lambda_i^* &= 0, \forall i. \end{aligned} \tag{15}$$

According to the complementary slackness conditions [15] for the optimal solution $P_{R_i}^{S_j *}$ and the dual variables λ_i^*, we can conclude that

$$\begin{cases} if \quad f'(P_{R_i}^{S_j *}) > 0, \text{ then } \; P_{R_i}^{S_j *} = 0, \\ if \quad P_{R_i}^{S_j *} > 0, \qquad \text{then } f'(P_{R_i}^{S_j *}) = 0. \end{cases} \tag{16}$$

From (16), we conclude that the gradient vector of $f'(P_{R_i}^{S_j})$ at the optimum should be equal to 0 when $P_{R_i}^{S_j *} > 0$. Then we can derive the following equation:

$$(1 + \sum_{n=1}^{N} \frac{x_n}{\alpha_n x_n + \beta_n})^{1+\tau\theta_j} = \frac{\tau \mu_j \theta_j \beta_i}{(\alpha_i x_i + \beta_i)^2}, \tag{17}$$

where $\tau = \frac{1}{N+1}$, $\alpha_i = \alpha_{R_i}^{S_j}$, $\beta_i = \beta_{R_i}^{S_j}$, $x_i = P_{R_i}^{S_j*}$. In (17), let $i = 1$, we get

$$\left(1 + \sum_{n=1}^{N} \frac{x_n}{\alpha_n x_n + \beta_n}\right)^{1+\tau\theta_j} = \frac{\tau\mu_j\theta_j\beta_1}{(\alpha_1 x_1 + \beta_1)^2}. \tag{18}$$

Since x_i is assumed larger than 0, we have $\alpha_i x_i + \beta_i > 0$. Then we can get

$$x_i = \frac{\sqrt{\frac{\beta_i}{\beta_1}}(\alpha_1 x_1 + \beta_1) - \beta_i}{\alpha_i}, i > 1. \tag{19}$$

Substituting (19) into (17), we can obtain the following equation with one variable x_1

$$\psi_1(\alpha_1 x_1 + \beta_1)^{\frac{2}{\psi_3}} + \psi_2(\alpha_1 x_1 + \beta_1)^{\frac{2}{\psi_3}-1} - \psi_4^{\frac{1}{\psi_3}} = 0, \tag{20}$$

where

$$\psi_1 = 1 + \sum_{i=1}^{N} \frac{1}{\alpha_i}, \quad \psi_2 = -\sum_{i=1}^{N} \left(\frac{\sqrt{\beta_1\beta_i}}{\alpha_i}\right), \quad \psi_3 = 1 + \tau\theta_j, \quad \psi_4 = \tau\mu_j\theta_j\beta_1.$$

It's worth noting that x_i is assumed positive in the foregoing derivations from (17) to (20). But solving function (20) and (19) can not guarantee $x_i > 0$. If there exists $x_i \le 0$, (17) does not hold and the derivation is wrong. In view of this situation, we divide the index of relays $\{1, ..., N\}$ into two subsets R_1 and R_2, such that $x_i = 0, \forall i \in R_1$, and $x_i > 0, \forall i \in R_2$. Then, the equation in (17) turn to the following:

$$(1 + \sum_{n \in R_2} \frac{x_n}{\alpha_n x_n + \beta_n})^{1+\tau\theta_j} = \frac{\tau\mu_j\theta_j\beta_i}{(\alpha_i x_i + \beta_i)^2}. \tag{21}$$

Based on (21), the relay index set in the derivations from (18) to (20) is also replaced by R_2. As a result, our aim is to find out R_2 efficiently. From (16), we can infer when $P_{R_i}^{S_j*} = 0$, $f^{'}(P_{R_i}^{S_j*}) \ge 0$. Based on this property, the simplest method is to enumerate all possible pairs of R_1 and R_2 and checking whether the optimality condition is satisfied. That is, $P_{R_i}^{S_j*} > 0, \forall i \in R_2$ and $f_i'(P_{R_i}^{S_j*}) \ge 0, \forall i \in R_1$. However, the time complexity of enumerating all pairs is exponential. Next, we will improve the algorithm to get R_1 and R_2 in polynomial time. We proved the following two lemmas where the proofs have been omitted for space.

Lemma 1. *If* $1 - \frac{\tau\mu_j\theta_j}{\beta_i} \ge 0$, *then we must have* $x_i = 0$.

Lemma 2. *If* $\beta_k \ge \beta_l$ *and* $x_k > 0$, *then we must have* $x_l > 0$.

From Lemma 1, we can see that the relay selection policy depends on the channel state and the delay requirement. If the channel state is worse and the delay requirement is loose, $1 - \frac{\tau\mu_j\theta_j}{\beta_i}$ turns out to be nonnegative and the relay node i tends not to supply any power to the k-th user. Otherwise, the resource allocation policy will allocate power for the k-th user to satisfy its stringent QoS requirements. Through the properties Lemmas 1 and 2 imply, we give the following algorithm to obtain the optimal power solution $P_{R_i}^{S_j*}$.

Algorithm 1. Search for Optimal Power Control

1: Initialize $R_1 = R_2 = \emptyset$.
2: Compute $\tau\mu_j\theta_j/\beta_i$, for $i = 1, ..., N$.
3: If $1 - \tau\mu_j\theta_j/\beta_i \geq 0$, $R_1 = R_1 \cup \{i\}$, else $R_2 = R_2 \cup \{i\}$.
4: Set $P_{R_k}^{S_j*} = 0$ for $\forall k \in R_1$.
5: Sort the indices in R_2 in the decreasing order of β_i, to obtain the permutation π.
6: Initialize s=1.
7: For $\forall k \in R_2$, solve Eqs. (19) and (20) to get the optimal solution $P_{R_k}^{S_j*}$. If there exists $k \in R_2$, such that $P_{R_k}^{S_j*} \leq 0$, update $P_{R_{\pi(s)}}^{S_j*} = 0$, $S_1 = R_1 \cup \{\pi(s)\}$, $R_2 = R_2 - \{\pi(s)\}$, $s = s + 1$, and repeat this step.
8: Calculate $f_k^{'}(P_{R_k}^{S_j*})$, $\forall k \in R_1$. If there exists $k \in R_1$, such that $f_k^{'}(P_{R_k}^{S_j*}) < 0$, update $P_{R_{\pi(s)}}^{S_j*} = 0$, $R_1 = R_1 \cup \{\pi(s)\}$, $R_2 = R_2 - \{\pi(s)\}$, $s = s + 1$, goto step 7; else, output the resultant $P_{R_i}^{S_j*}, \forall i$.

3.3 Stochastic Resource Allocation

To implement the gradient iteration (10), we need the explicit knowledge of fading channel cdf to evaluate the expected values. However, in some practical mobile applications, it is infeasible to obtain the channel cdf. As it turns out, the problem without the knowledge of channel cdf can be solved through the stochastic optimization theory [10]. By this theory, $\mathbb{E}_h$ is dropped from (10) and a stochastic gradient iteration algorithm based on per slot fading realization is put forward as follows:

$$\mu_j[t+1] = \left[\mu_j[t] + s \cdot \left(e^{-\theta_j r_j} - e^{-\theta_j \bar{a}_j}\right)\right]^+, \tag{22}$$

where t is the iteration index and s is a positive step-size. It only requires the fading state of the channels at the current iteration, which can be easily measured.

4 Numerical Results

In this section, we provide some numerical results to evaluate the performance of the proposed power allocation policy. Throughout our simulation, we consider a wireless relay network with five users and three relays distributed in a two-dimensional region. The relays are fixed at coordinates (3,1), (3,2) and (3,3). The source and destination nodes are deployed at the lines (0,0)–(0,4) and (6,0)–(6,4), respectively. The average SNR for the link between nodes i and j is given by $\gamma_{ij} = \frac{\bar{\gamma}}{((x_i - x_j)^2 + (y_i - y_j)^2)^{\frac{n}{2}}}$ where the reference SNR $\bar{\gamma}$ is 10 dBW and the loss exponent n is 3.6. The channel fading processes are generated from quasi-static frequency-selective Rayleigh fading channels with γ_{ij}. The variances of AWGN N_{R_i} and N_{D_j} are assumed to be 1. The transmit power P_{S_j}, $j = 1, ..., 5$, are chosen to be 1 W. The unit for the power is Watt in our simulation.

On the premise that the channel fading cdf was unknown in the simulation, the proposed stochastic scheme was used to learn the time varying channel states to approach the optimal resource allocation policy. Figure 1 shows the evolution of Lagrange multiplier μ_2 of each iteration when $\bar{a}_j = 0.1$ and $\theta_j = 0.1$. The curve verifies the stochastic convergence of the iterations algorithm, and we can observe that the Lagrange multiplier μ_2 stochastically converges to its corresponding optimal value $\mu_2^* = 0.5987$. Note that due to the dynamics of per slot fading realization, the value of μ_2 fluctuates around its optimal value within a small neighborhood proportional to the stepsize s.

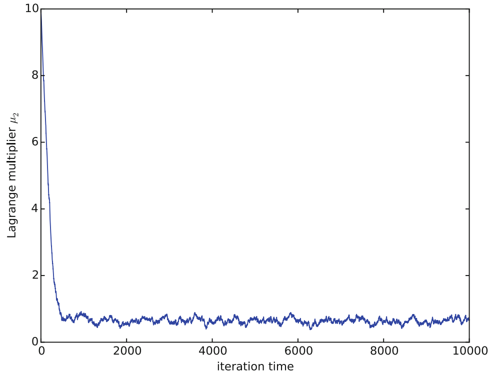
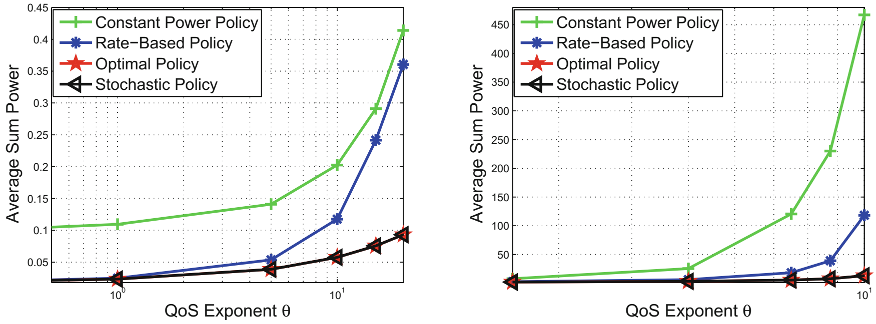


Fig. 1. Stochastic convergence of Lagrange multiplier μ_2

To gauge the performance of the proposed algorithm, we compare it with two other power allocation policies. The first scheme named constant power policy, in which each relay use the same transmit-power to transmit signals from source to destination. The second scheme asks to minimize the whole power cost while satisfying a minimum ergodic rate constraints of each source-destination pair, named rate-based policy. The optimal policy proposed in (10), stochastic policy proposed in (22), constant power policy and rate-based policy are compared in terms of the minimum average sum power while satisfying the same delay QoS requirements. We ran the four policy with the constrains of effective capacity $\bar{a}_j = 0.1$ and $\bar{a}_j = 0.5$, $j = 1, ..., 5$. Numerical results are shown in Fig. 2(a) and (b), respectively. Notice that the optimal policy demonstrates the same performance with the stochastic one, which proves that the proposed stochastic scheme can approach the optimal policy via learn the channel fading knowledge on the fly. It is shown that the allocated power of the proposed policy increases with the QoS exponent θ. This illustrates that more power must be consumed in order to guarantee the more strict QoS requirements. Also the proposed policy outperforms the other two policies obviously in power saving. Additionally, the difference value between the two policies increases with the delay QoS exponents.



(a) (b)

Fig. 2. The power allocation policy when $\bar{a}_j = 0.1$ (a) and $\bar{a}_j = 0.5$ (b)

5 Conclusion

We have formulated a convex optimization framework for resource allocation by taking the delay QoS requirement into account in wireless relay networks. Based on the framework, we have proposed a power control policy with the objective of minimizing the overall power consumption while fulfilling the minimum Qos requirement. By using the dual decomposition method, we solved the optimization problem and derived a optimal power control policy. Furthermore, we proposed a stochastic method that can learn the fading state of the channels and carry out the optimal strategy immediately. It has been shown that our proposed policy exhibits excellent performance of power saving compared with constant power policy and rate-based policy.

Acknowledgments. This work was supported by the National Science Foundation of China (No. 61201269, No. 61571272, No. 61403230), 2014 Shandong housing and urban-rural development soft science research project (No. RK015), the Natural Science Foundation of Shandong Province (Doctoral Foundation)(No. BS0135DX013), and the China Postdoctoral Science Foundation funded project (No. 2015M582104).

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