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A New Distributed Robust Power Control for Two-Layer Cooperative Communication Networks in Smart Grids with Reduced Utility Costs

Chang Xiong, Yixin Su *, Danhong Zhang, Lan Chen, Huajie Zhang and Qi Li

School of Automation, Wuhan University of Technology, Wuhan 430070, China
* Correspondence: suyixin@whut.edu.cn

Abstract: The packet loss during transmission of load control commands can lead to regulation errors in the smart grid and increase the cost of utility agencies due to the purchase of additional automatic generation control (AGC) services. In this paper, a two-layer cooperative communication network between the utility company and relays is presented. The utility company rents the relay to assist with the downlink transmission to improve the reliability of communication and reduce the data transmission cost due to packet loss. Furthermore, the uncertainty of channel gain is considered, and a two-tier game model is established. A distributed robust power control algorithm based on the continuous convex approximation method is proposed to obtain the optimal relay power allocation and price. Through the simulation analysis of the proposed scheme and the two comparison schemes, the cost of the utility company was reduced by 6% and 21%, and the standard deviation of income value between the relays was reduced by 40% and 48%, respectively.

Keywords: communication network; cooperative relay; two-layer game; smart grid

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1. Introduction

Smart grids, as typical cyber–physical systems, comprise energy management systems and demand-side communication systems [1]. Bidirectional communications between the electricity utility and customers enable engagement in demand response. Communication is important to the precision and effectiveness of demand response [2]. In general, smart grids are built on layered communication networks, including wide area networks (WANs), neighborhood area networks (NANs), and home area networks (HANs) [3,4]. It is worth noting that the distributed framework is a typical communication framework for demand-side response and efficient data aggregation schemes in smart grids [5,6]. In these two works, distributed frameworks refer to typical peer-to-peer networks with local computation, which inherit the merits of avoiding single-point failures. The other advantage of adopting distributed communication networks for smart grids is more flexible pricing which enables huge discounts on trading costs [7,8]. However, when the data aggregation unit (DAU) receives a large quantity of data over a short period of time, it will lead to congestion and packet loss in the transmission of smart grid control commands and meter data [9,10], and utility companies have to pay more for automated generation control (AGC) service. In [11], the influence of supply cost and packet loss on demand-side control are studied. According to the results, the estimated demand is normally distributed, and the supply cost rises in proportion to the rate of packet loss. The packet loss caused by failures in communication between users and utilities with regard to the dependability of wireless communication network demand replies is comprehensively analyzed in [12]. The results show that the error of demand-side control is increased by the packet loss rate. Apart from the aforementioned characteristics, communication resource allocations for smart grids have some specific features. In [13], the unpredictability of two-way communications among the grid's data network components is presented for smart grid systems with efficient distributed energy resources. In [14], a cognitive ratio with the spectrum detection and channel method for smart grids is implemented to increase communication dependability. By jointly considering both sample rate regulations and dynamic channel accessibility, the system utility maximization issue in energy harvesting CRSNs is explored in [15]. Moreover, the aggregate rates of all cellular nodes are optimized to allocate communication channels and manage to transmit power, while maintaining the dependability criteria of the RTP operation. A radio resource allocation method is suggested in [16]. In [17], a unique expense methodology is proposed for allocating cloud computing resources for demand-side management. while taking the load profile of computing devices and features of cloud computing cases into account.

In recent years, cooperative communication technologies have exhibited superior performance in achieving spatial diversity in order to lower bit failure rates in demand-side communications [18–20]. Based on the fundamental technologies, a relay selection strategy was proposed to enhance the end-to-end packet transmission delay, the energy efficiency of NAN and NHAN, and throughput in [21]. In [3], the demand-side cooperation relay network's resource allocation issues are investigated in depth using bargaining models. Since relaying symbolizes the sharing of resources between DAUs and relays, both relay selection and resource allocation are concurrently considered. In [22], an artificial bee colony (ABC) method is used to study the joint relay allocation and resource management in cooperative communications systems. In [23], a cooperative relay strategy and a relay selection method are adopted to enhance the secure transmission rate. In [24], a cooperative physical security protection relay selection technique is presented to improve the communication safety of industrial wireless nodes.

Pioneering research investigations have revealed that cooperative communication technologies can significantly decrease the packet loss rate. Consequently, the demand-side control errors caused by data congestion and costs of utility companies can be reduced. However, the DAUs used for cooperative communication technologies have limits on choosing relays for collaborative transmission, as can be seen in many classic models in previous work. Typical examples are provided in [22–24]. In conventional studies, each DAU can only decide whether to cooperate with the relay or not. When DAU data packet congestion is not serious, the full power of the relay leased by the DAU will lead to channel capacity redundancy and relay resource waste. In addition, the channel gain showcases randomness in the actual environment. To address these critical issues, a two-tier game scheme between the utility companies and relays is proposed for two-layer cooperative communication networks in smart grids to reduce the costs of utility agencies The new distributed robust power control is established based on the distribution of relay power. The main contributions of this paper can be mainly summarized into the following two points:

- A cooperative communication network model is established by considering the decision making from the utility companies and relay power allocations, which has never been proposed before. The new model improves the flexibility of power allocation options and further reduces the expenses of utility agencies.
- Due to the randomness of channel gain, robust constraints are introduced into the optimization model and transformed. A distributed algorithm is created to maximize the relay income and minimize the costs of utility companies.

The rest of this paper is structured as follows: Section 2 establishes the cooperative communication network model. In Section 3, the cost model of the utility company is converted, and a two-layer game model is established. Section 4 gives the simulations of the suggested scheme. Section 5 draws the conclusions.

2. System Model

2.1. Network for Demand-Side Cooperative Communications

We consider a cooperative communication network model as shown in Figure 1, which consists of N DAUs and N gateways assisted by M relays. The network uses frequency division multiplexer, and each DAU is given access to an orthogonal channel for communication between the DAU, relay, and gateway. The relay relationship is defined as a matrix $\alpha = \{\alpha_{i,k}\}_{M\times N}$, where $\alpha_{i,k}$ is the power allocation ratio of relay i to DAU k. In [22], the relay relationship follows the constraints: each relay serves multiple DAUs, while just one relay can be chosen by each DAU. To enhance the profit and robustness of the system, we adjust the constraint so that each relay would serve multiple DAUs, and each DAU can have several relays. Such an assumption is reasonable as it is similar to the multi-point to multi-point technique in multicast [25]. Multicast is an effective transmission method for group communication. For example, multi-point video conferencing uses this technology. Multi-point video conferencing usually has multiple concurrent video sources, and participants need to receive video data from multiple other users. Typically, each receiver can receive data sent by more than one sender, and at the same time, each sender can send data to more than one receiver. In this model, the DAUs can be considered as multiple senders, and the relays act as multiple receivers. Correspondingly, the following constraints can be obtained:

$$\begin{Bmatrix} \sum_{k=1}^{N} \alpha_{i,k} \leq 1 \\ 0 \leq \alpha_{i,k} \leq 1 \end{Bmatrix} \tag{1}$$

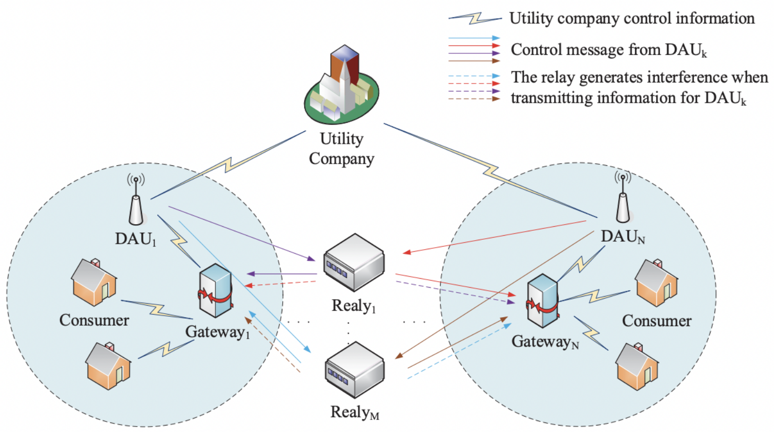

Figure 1. Cooperative communication network model.

Based on [26], the gateway's channel capacity k is determined by the maximum combination ratio:

$$c_k = \frac{W}{2} \log_2 1 + p_0 g_{k,k}^d + \sum_{i=1}^{M} \alpha_{i,k} p g_{i,k} \tag{2}$$

where p_0 is the DAU's transmission power, p is the relay's transmission power, $g_{k,k}^d$ is the channel gain from k of DAU to k of the gateway, and $g_{i,k}$ represents the channel gain from relay i to gateway k. The channel gain has complex uncertainty, which can be approximately expressed as

$$g = K(\bar{g} + c)d^{-\kappa} \tag{3}$$

where d is the distance between two communication nodes, and κ stands for the exponents of path loss. K, determined by carrier frequency and antenna gain, represents the path loss constant. In the case of a small range of Rayleigh fading, $\bar{g}$ represents a random value subject to exponential distribution, and c represents the highest estimate error.

Supposing τ is the interval between the channel capacity and reception rate. Without loss of generality, let $\tau = \frac{1}{\ln 2}$, and then $\hat{C_k} = C_k \tau$.

2.2. Packet Loss Model

Without sacrificing generality, we solely examine packet loss in downlink communication and obtain the packet loss rate as

$$p^1 = \frac{T^{in} - R_k h}{T^{in}} \tag{4}$$

where T^{in} denotes the DAU's arriving rates, R_k is the gateway's receiving rate, and h is the correct transmission ratio between the gateways and the users.

Supposing the noise strength is N_0, the gateways' receiving rates with decode-and-forward relays are defined as [27]

$$R_k = \frac{1}{2} \ln 1 + \frac{p_0 g_{k,k}^d}{N_0 + \sum_{i=1}^M (1 - \alpha_{i,k}) p g_{i,k}} + \frac{\sum_{i=1}^M \alpha_{i,k} p g_{i,k}}{N_0 + \sum_{i=1}^M (1 - \alpha_{i,k}) p g_{i,k}} \tag{5}$$

Combining with (4), we have

$$p^1 = h(1 - \frac{1}{2T^{in}} \ln 1 + \frac{p_0 g_{k,k}^d}{N_0 + \sum_{i=1}^M (1 - \alpha_{i,k}) p g_{i,k}} + \frac{\sum_{i=1}^M \alpha_{i,k} p g_{i,k}}{N_0 + \sum_{i=1}^M (1 - \alpha_{i,k}) p g_{i,k}}) \tag{6}$$

Because of the uncertainty of channel gain in the actual communication environment, the target of interrupt threshold $\varepsilon \in (0, 1)$ is proposed to constrain the channel QoS of DAU k. The interrupt probability of the DAU k channel should meet:

$$P_r\{R_k \geq \Gamma\} \geq 1 - \varepsilon \tag{7}$$

When P_r is greater than $1 - \varepsilon$, the communication is considered to be effective. Here, P_r is the probability that the receiving rate R_k of the gateway is greater than the threshold Γ.

2.3. Cost Scheme of the Utility Agencies

As shown in (6), P_1 is related to α, and it can be written as $P^1(\alpha)$. The expense of the utility agencies with respect to each gateway k is defined as

$$Z_k(\alpha) = p_a \Phi(P^1(\alpha)) + Z_0 \tag{8}$$

where p_a represents the AGC service's price per unit fraction. Z_0 is the cost of renting relay power; we define Z_0 as

$$Z_0 = \sum_{i=1}^{M} \alpha_{i,k} u_i \tag{9}$$

where u_i represents the unit price of leased relay power. In particular, the relay adjusts u_i according to the revenue model, and $\Phi(P^1(\alpha))$ increases the packet loss rate P^1. Therefore, cooperative transmission through a leased relay can reduce the packet loss rate P^1, thus decreasing the cost of purchasing AGC ancillary services, and the utility company needs to pay corresponding compensation to the relay. According to the results of previous work, such as [3], the tracking error would be determined to have a normal distribution. When the power company purchases $\mu + t\sigma$ AGC service, $t \in (1, 2, 3)$, the probability of providing ancillary services can be guaranteed to reach 67%, 95%, and 99%, respectively. Therefore, $\Phi(P^1(\alpha))$ is given by

$$\Phi(P^1(\alpha)) = \mu + t\sigma \tag{10}$$

where μ and σ represent expectation and variance, respectively. Here, c, d, e, and f are constants. In MATLAB and Easyfit, the packet loss rate $\Phi(P^1(\alpha))$ is set from 1% to 10%, respectively, and the following can be obtained:

$$\mu = cP^1(\alpha) - d \tag{11}$$

and

$$\sigma = eP^1(\alpha) - f \tag{12}$$

2.4. Revenue Model of Relay

The revenue of the relay i is defined as

$$max\ U_i = U_d - U_r \tag{13}$$

where U_d represents the profit obtained from the utility agencies, which is defined as

$$U_d = \sum_{k=1}^{N} \alpha_{i,k} p u_i \tag{14}$$

In order to avoid the unlimited rise of the relay price, we introduce the interference cost U_r between relays. It is defined as

$$U_r = \sum_{k=1}^{N} \frac{p(1-\alpha_{i,k})}{n-1} \frac{\ln u_i}{\frac{1}{M-1}\sum_{-i} \ln u_i} u_i \tag{15}$$

If the relay i uses the power of $\alpha_{i,k}p$ to forward data for DAU k, then the power of $(1 - \alpha_{i,k})p$ will be transmitted for devices other than DAU k and can be considered as interference for DAU k. Relay i can be expressed as $\sum_{k-1}^{N}(1-\alpha_{i,k})p$ and further approximated as $(N-1)p\sum_{k=1}^{N}\alpha_{i,k}$; hence, we have to divide by $N-1$ to avoid double counting. Here, $\frac{\ln u_i}{\frac{1}{M-1}\sum_{-i} ln u_i} u_i$ constitutes a noncooperative game between relays.

3. Game Model and Solution

3.1. A Two-Layer Game Model between Utility Company and Relays

A cost optimization model can be established to reduce the costs of utility companies and increase the benefits of relays. This section will derive the optimal solution for power allocation and relay pricing. Firstly, we establish a two-layer model. The lower layer minimizes the expense of utility agencies by optimizing the power allocation ratio α, and the optimization issue can be derived as

$$\begin{aligned} &(\text{P1})\ \min \sum_{k=1}^{N} Z_k(\boldsymbol{\alpha}) \\ &\text{s.t. } \sum_{k=1}^{N} \alpha_{i,k} \le 1, (i = 1, 2\ldots, M) \\ &0 \le \alpha_{i,k} \le 1, (i = 1, 2\ldots, M) \\ &P_r\{R_k \ge \Gamma\} \ge 1 - \varepsilon \end{aligned} \tag{16}$$

where

$$Z_k(\alpha) = p_a h(1 - \frac{1}{2T^{in}} \ln{(1 + \frac{p_0 g_{k,k}^d}{N_0 + \sum_{i=1}^{M}(1-\alpha_{i,k})pg_{i,k}} + \frac{\sum_{i=1}^{M}\alpha_{i,k}pg_{i,k}}{N_0 + \sum_{i=1}^{M}(1-\alpha_{i,k})pg_{i,k}}))} + Z_0 \tag{17}$$

At the upper layer, the relay needs to increase the profit by adjusting the price of relay power u_i, and the optimization issue is denoted as follows:

$$\begin{aligned}(\mathrm{P2})\max U_i = &\sum_{k=1}^{N} \alpha_{i,k} p u_i - \\ &\sum_{k=1}^{N} \frac{p(1-\alpha_{i,k})}{n-1} \frac{\ln u_i}{\frac{1}{M-1}\sum_{-i} \ln u_i} u_i\end{aligned} \tag{18}$$

3.2. Lower Layer Optimization

(1) Transformation of objective functions: (P1) is a non-convex optimization issue and can be transformed into a new objective function through a continuous convex approximation algorithm. In (P1), R_k can be defined as:

$$\begin{aligned}R_k = \tfrac{1}{2}\ln\Bigg(1 + &\tfrac{p_0 g_{k,k}^d}{N_0 + \sum_{i=1}^{M}(1-\alpha_{i,k}) p g_{i,k}} \\ &+ \tfrac{\sum_{i=1}^{M} \alpha_{i,k} p g_{i,k}}{N_0 + \sum_{i=1}^{M}(1-\alpha_{i,k}) p g_{i,k}}\Bigg)\end{aligned} \tag{19}$$

In the continuous convex approximation method, we have

$$\delta \log z + \beta \leq \log(1+z) \tag{20}$$

The objective function is optimized by adjusting the independent variable z, and z_0 is the optimal answer of the transformation issue. We need to determine the values of δ and β, where $\delta \geq 0$. When z is equal to z_0, we substitute it into (20), and we have

$$\left(\frac{z}{z_0}\right)^{\delta} \leq \frac{1+z}{1+z_0} \tag{21}$$

According to (21), we can obtain:

(a) All effective coefficients meet (21);
(b) When $\delta \geq 1$, $(\frac{z}{z_0})^{\delta}$ is a concave function;
(c) At $z = z_0$, the tangent of $(\frac{z}{z_0})^{\frac{z}{1+z_0}}$ is $\frac{1+z}{1+z_0}$.

From the above statements, we conclude that $\delta = \frac{z_0}{1+z_0}$ is the maximum value that satisfies (21). Hence, the coefficients are selected as follows:

$$\begin{cases} \delta = \frac{z_0}{1+z_0} \\ \beta = \log(1+z_0) - \frac{z_0}{1+z_0}\log z_0 \end{cases} \tag{22}$$

Substituting (20) into (16), the objective function is represented as

$$\begin{aligned}Z_k = &-p_a\left(a\left(1 - \frac{1}{2T^{\mathrm{in}}}\left(\delta \ln \mathrm{SINR}_i(\alpha_{i,k}) + \beta\right)\right) - b\right) \\ &- \sum_{i=1}^{M} \alpha_{i,k} p u_i\end{aligned} \tag{23}$$

where a and b are constants, and the signal-to-interference plus noise ratio (SINR) is denoted by

$$\begin{aligned}\mathrm{SINR}_i(\alpha_{i,k}) = &\frac{p_0 g_{k,k}^d}{N_0 + \sum_{i=1}^{M}(1-\alpha_{i,k}) p g_{i,k}} \\ &+ \frac{\sum_{i=1}^{M} \alpha_{i,k} p g_{i,k}}{N_0 + \sum_{i=1}^{M}(1-\alpha_{i,k}) p g_{i,k}}\end{aligned} \tag{24}$$

The optimization problem after transformation is not convex about $\alpha_{i,k}$. Let $\widetilde{\alpha}_{i,k} = \log_2 \alpha^{i,k}$. Then, the new objective function can be represented as

$$\begin{aligned} Z_k = & - p_a\left(a\left(1 - \frac{1}{2T^{\text{in}}}\left(\delta \ln \text{SINR}_i\left(e^{\widetilde{\alpha}_{i,k}}\right) + \beta\right)\right) - b\right) \\ & - \sum_{i=1}^{M} e^{\widetilde{\alpha}_{i,k}} p u_i. \end{aligned} \tag{25}$$

(2) Transformation of constraints: Multiple uncertain channel gain $g^d_{k,k}$, $g_{i,k}$ exists in (19), and it is difficult to obtain an analytical expression. The channel gain vector is given as follows:

$$\begin{aligned} \boldsymbol{g_k} &= [g_{1,k}, g_{2,k} \cdots g_{M,k}] \\ \boldsymbol{g_n} &= [g_{1,1}, g_{2,2} \cdots g_{N,N}] \end{aligned} \tag{26}$$

Under the condition of Rayleigh distribution, we calculate the expectations of the channel gain vectors $\boldsymbol{g_k}$ and $\boldsymbol{g_n}$:

$$\mathbb{E}\{\boldsymbol{g_k}\} = \sqrt{\frac{\pi}{2}}\widetilde{\boldsymbol{g}}_{\boldsymbol{k}}, \mathbb{E}\{\boldsymbol{g_n}\} = \sqrt{\frac{\pi}{2}}\widetilde{\boldsymbol{g}}_{\boldsymbol{n}} \tag{27}$$

where $\widetilde{g} = Kd^{-\kappa}$.

Theorem 1. *For any interrupt probability threshold $\varepsilon \in (0,1)$, the distributed robust opportunity constraint*

$$\inf_{G_0 \sim (\bar{G}_0, H)_D} P_r\left\{G_0^T A_0 \leq N_0\right\} \geq 1 - \varepsilon \tag{28}$$

can be equivalent to a convex second-order cone constraint:

$$\sqrt{\frac{1-\varepsilon}{\varepsilon}}\sqrt{A_0^T H A_0} + \hat{\varphi}(A_0) - N_0 \leq 0 \tag{29}$$

where $(.)_D$ denotes an entire family of probability distributions on data G_0, and $\hat{\varphi}(A_0) = \bar{G}_0^T A_0$, $A_0 = A - \Gamma MB$. $\bar{G}_0$ is a vector composed of the mean of G_0, H is the covariance matrix of G, and $A = [\alpha_{1,k}, \alpha_{2,k} \ldots, \alpha_{M,k}]$, $B = [(1-\alpha_{1,k}), (1-\alpha_{2,k}) \ldots, (1-\alpha_{M,k})]$.

Proof of Theorem 1. We denote H_f as a full-rank matrix such that $H = H_f H_f^T$ and $G_0 = \bar{G}_0 + H_f \varpi$, where ϖ is a random variable, $\mathbb{E}\{\varpi\} = 0$, and $\mathbb{D}\{\varpi\} = \mathbf{I}$ are discussed in the following two cases:

Case A: $H_f^T A_0 \neq 0$. According to the results in [25], there are:

$$\begin{aligned} & \sup\nolimits_{G_0 \sim (G_0, H)_D} P_r\{G_0^T A_0 > N_0\} = \\ & \sup\nolimits_{\varpi \sim (0, I)} P_r\left\{\varpi^T H_f^T A_0 > -\bar{G}_0^T A_0 + N_0\right\} = \tfrac{1}{1+A_0^2}, \end{aligned} \tag{30}$$

where $q^2 = \inf_{\varpi^T H_f^T A_0 > -\hat{G}_0{}^T A_0 + N_0} \|\varpi\|^2$. If $G_0 A_0 - N_0 > 0$, the lower bound is $q^2 = 0, \varpi = 0$. If $G_0 A_0 \leq 0$, calculate the square of the distance from the origin to the hyperplane $\left\{\varpi : \varpi^T H_f^T A_0 > -\bar{G}_0^T A_0 + N_0\right\}$. It is easy to obtain $q^2 = \frac{(\bar{G}_0^T p - N_0)^2}{A_0^T H A_0}$. Therefore, (28) is true when $\frac{1}{1+q^2} \leq \varepsilon$. If and only if, $\bar{\Phi}(A_0) \leq N_0$, $-\bar{\Phi}(A_0) \geq \sqrt{\frac{1-\varepsilon}{\varepsilon}}\sqrt{A_0^T H A_0}$, (28) and (29) are equivalent.

Case B: $H_f^T A_0 = 0$. If $\Phi(A_0) \leq N_0$, there is $\inf_{g \sim (\hat{g}, H)_D} P_r\{G_0^T A_0 \leq 0\} = 1$. At this time, (28) and (29) are still equivalent. □

Through the transformation of objective functions and constraints, the cost objective function of the utility company is equivalent to

$$
\begin{aligned}
&(\text{P3})\ \max -p_a\left(a\left(1-\tfrac{1}{2T^{\text{in}}}\left(\delta \ln \text{SINR}_i\left(e^{\widetilde{\alpha}_{ik}}\right)+\beta\right)\right)-b\right) \\
&-\textstyle\sum_{i=1}^{M} e^{\widetilde{\alpha}_{i,k}} pu_i \\
&\ \text{s.t. } \textstyle\sum_{k=1}^{N} \alpha_{i,k} \le 1, (i=1,2\ldots,M) \\
&0 \le \alpha_{,ik} \le 1, (i=1,2\ldots,M) \\
&\sqrt{\tfrac{1-\varepsilon}{\varepsilon}}\sqrt{A_0^T H A_0}+\hat{\varphi}(A_0)-N_0 \le 0, (k=1,2\ldots,N).
\end{aligned}
\tag{31}
$$

After the above transformations, the optimization problem (P3) is convex.

(3) Optimization solution: To solve the transformed optimization issue (P3), a distributed iterative algorithm with successive convex approximation is introduced, and then the dual decomposition method is used to obtain the optimal answer. The partial Lagrange function of (P3) is denoted by

$$
\begin{aligned}
(\text{P4})L = -\sum_{k=1}^{N} Z_k - \lambda_i\left(\sum_{k=1}^{N}\alpha_{i,k}-1\right)- \\
\sum_{k=1}^{N}\nu_k\left(\sqrt{\frac{1-\varepsilon}{\varepsilon}}\sqrt{A_0^T H A_0}+\hat{\varphi}(A_0)-N_0\right).
\end{aligned}
\tag{32}
$$

Define

$$
\begin{aligned}
(\text{P5})B = -\,Z_k - \lambda_i\alpha_{i,k} - \\
v_k(\sqrt{\frac{1-\varepsilon}{\varepsilon}}\sqrt{A_0^T H A_0}+\hat{\varphi}(A_0)-N_0).
\end{aligned}
\tag{33}
$$

and $D(\lambda,\nu) \mid= \max_\alpha L(\widetilde{\boldsymbol{\alpha}},\lambda,\nu)$, where (P4) is determined by the dual problem (P6).

$$
\begin{aligned}
&(\text{P6})\ \min D(\lambda,\nu) \\
&\quad \text{s.t. } \lambda_i \ge 0, (i=1,2\ldots,M) \\
&\quad\quad \nu_k \ge 0, (k=1,2\ldots,N)
\end{aligned}
\tag{34}
$$

The dual problem (P6) is solved by power allocation and multiplier update. Here, $e^{\widetilde{\alpha}_{i,k}}$ stands for the optimization of power, and we have

$$
e^{\widetilde{\alpha}_{i,k}} = \frac{-B_2+\sqrt{B_2^2+4T^{\text{in}}B_1\left(2T^{\text{in}}B_3-\frac{p_a a\delta_k A_1}{pu_i-(\lambda_i+v_k C_1)}\right)}}{C_2}
\tag{35}
$$

where

$$
B_1 = p^2 g_{i,k}
\tag{36}
$$

$$
B_2 = 2T^{\text{in}}\left(N_0+p_a g_{k,k}^d+\sum_{i=1}^{M} p g_{i,k}\right)
\tag{37}
$$

$$
B_3 = \left(N_0+\sum_{i=1}^{M} p g_{i,k}-\sum_{l\neq i}^{M} e^{\widetilde{\alpha}_{l,k}} p g_{l,k}\right),
\tag{38}
$$

$$
A_1 = p g_{i,k}\left(N_0+\sum_{i=1}^{M} p g_{i,k}\right)+p_a g_{k,k}^d\Big)
\tag{39}
$$

$$A_2 = N_0 + \sum_{i=1}^{M} p g_{i,k} - \sum_{l \neq i}^{M} e^{\widetilde{\alpha}_{l,k}} p g_{l,k} \tag{40}$$

$$A_3 = p_a g_{k,k}^d + \sum_{l \neq i}^{M} e^{\widetilde{\alpha}_{l,k}} p g_{l,k} \tag{41}$$

$$C_1 = \sqrt{\frac{1-\varepsilon}{\varepsilon}} \sqrt{2 - \frac{\pi}{2}} \frac{\Gamma}{\Gamma+1} + \left(\frac{\Gamma}{\Gamma+1} \right)^2 p g_{i,k}. \tag{42}$$

The update of Lagrangian multipliers λ_i and ν_k can be shown below:

$$\lambda_i(t+1) = \lambda_i(t) + \theta \left(\sum_{k=1}^{N} \alpha_{i,k} - 1 \right) \tag{43}$$

$$\nu_i(t+1) = \nu_i(t) + \theta \left(\sqrt{\frac{1-\varepsilon}{\varepsilon}} \sqrt{A_0^T H A_0} + \hat{\varphi}(A_0) - N_0 \right) \tag{44}$$

where t represents the quantity of iterations, and θ represents the step size. After the dual issue is satisfied $|D(t+1) - D(t)| < \varepsilon$, the iteration will stop if ε is a positive number near 0.

3.3. Upper Layer Optimization

According to (18), a non-cooperative game is formulated between relays. Next, we need to prove the uniqueness of the game Nash equilibrium (NE). A vector $u^* = \left(u_1^*, u_2^* \ldots, u_M^*\right)$ is the NE if and only if

$$u^* = \arg\max U_i(u_i), i \in (0, 1, 2 \ldots, M). \tag{45}$$

First of all, the first derivative of the objective function U_i with respect to u_i is taken:

$$\frac{\partial U_i}{\partial u_i} = \sum_{k=1}^{N} \alpha_{i,k} p - \sum_{k=1}^{N} \frac{(M-1)p(1-\alpha_{i,k})}{N-1} \frac{1 + \ln u_i}{\sum_{-i} \ln u_i} \tag{46}$$

Let $\frac{\partial U_i}{\partial u_i} = 0$; the optimal response function can be obtained as:

$$f(u_{-i}) = e^{\frac{(N-1)\sum_{k=1}^{N} \alpha_{i,k} \sum_{-i} \ln u_i}{(N-A_i)(M-1)} - 1}, \tag{47}$$

where $A_i = \sum_{k=1}^{N} \alpha_{i,k}$.

Taking the second derivative of the objective function U_i with respect to u_i, we have

$$\frac{\partial^2 U_i}{\partial u_i^2} = -\sum_{k=1}^{N} \frac{(M-1)p(1-\alpha_{i,k})}{N-1} \frac{1}{u_i \sum_{-i} \ln u_i} \leq 0 \tag{48}$$

Since U_i with respect to u_i is lower than zero, U_i is convex with respect to u_i. It can be seen that the non-cooperative game has at the fewest one NE point. Then, we need to prove the one of a kind of NE. When u^* satisfies the following conditions, u^* is the only NE [28].

- Positivity: $I(\mathbf{u}) > 0$;
- Monotonicity: If $\mathbf{u} > \mathbf{u\prime}$, then $I(\mathbf{u}) > I(\mathbf{u\prime})$;
- Scalability: For all $\eta > 1$, $\eta I(\mathbf{u}) > I(\eta \mathbf{u})$.

Proof. *Positivity:* According to the best response function, we have

$$f(u_{-i}) = e^{\frac{(N-1)A_i \sum_{-i} \ln u_i}{(N-A_i)(M-1)} - 1}. \tag{49}$$

Since the exponential function is positive in any interval, it can be seen that $f(u_{-i}) > 0$.

Monotonicity: In order to facilitate the subsequent calculation, let $q = \frac{(N-1)A_i}{(N-A_i)(M-1)}$. Considering the partial derivative of $f(u_{-i})$ with respect to $u_j (j \neq i)$, it can be observed:

$$\frac{\partial f(u_{-i})}{\partial u_j} = e^{q\sum_{-i}\ln u_i - 1} q \frac{1}{u_j}. \tag{50}$$

The exponential function is positive, and according to (1), $0 \leq A_i \leq 1$; hence $q \geq 0$. Since u represents the electricity price, u_j is positive. According to the above conditions, we have:

$$\frac{\partial f(u_{-i})}{\partial u_j} \geq 0. \tag{51}$$

It is easy to obtain

$$\frac{\partial f(u_{-i})}{\partial u_i} = 0. \tag{52}$$

Therefore, monotonicity is proved.

Scalability: Comparing the magnitude of $\eta f(u_{-i})$ and $f(\eta u_{-i})$, we obtain:

$$\frac{\eta f(u_{-i})}{f(\eta u_{-i})} = \eta e^{q\sum_{-i}\ln u_i - q\sum_{-i}\ln \eta u_i} > 1. \tag{53}$$

When $\eta > 1$, we can obtain $\eta f(u_{-i}) > f(\eta u_{-i})$, and the scalability is proved. The uniqueness of NE is also proved. □

3.4. Distributed Robust Power Control Algorithm for Power and Price Optimization

In the previous studies, the power allocation and Lagrange multiplier were solved by transforming the power allocation objective function and constraint conditions, and the uniqueness of NE in the relay layer non-cooperative game was proved. Next, we propose the following distributed algorithm to realize the power distribution solution.

Firstly, we initialize the locations of DAUs, gateways, and relays, the leased relay power ratio α and the power unit price $\mathbf{u}$. Then, we calculate channel gain and utility company cost. Secondly, the DAUs need to rent the power ratio $\alpha_{i,k}$ and update the Lagrange multiplier and utility company cost. Finally, the relays adjust the price u_i to the utility company based on α. This calculation iterates until α and $\mathbf{u}$ converge, and the process is shown in Algorithm 1.

In each iteration of λ and ν, obtaining α and u requires $\mathcal{O}(T_1T_2)$ calculations. Suppose that Q is the number of iterations for the algorithm to converge. Therefore, the total complexity of Algorithm 1 is $\mathcal{O}(T_1T_2Q)$.

Algorithm 1: Distributed robust power control algorithm

Input: DAUs and gateways randomly generate positions, $N = 3$; Relays randomly generate positions, $M = 10$; Calculated channel gain g_{kk}, g_{ik}, $k \in \{1, 2 \ldots N\}$, $i \in \{1, 2 \ldots M\}$; Set the communication interruption threshold Γ and the number of iterations T_1 and T_2; Initialize the ratio of leased power α and power unit price $\mathbf{u}$

Output: Optimize rental power ratio α and electricity price $\mathbf{u}$

for $t_1 = 1; t_1 \leq T_1; t_1 = t_1 + 1$ **do**
  for $t_2 = 1; t_2 \leq T_2; t_2 = t_2 + 1$ **do**
    if $|D(t_2 + 1) - D(t_2)| < \varepsilon$ **then**
      Update the DAU leased power ratio α based on equation (35):
      Calculate the expense of the utility agency for this iteration based on (31);
      Update the Lagrange multipliers λ, ν according to (43) and (44).
    end
    else
      Transmit the decision results to relays;
    end
    The relays adjust the unit price of power through the decision of the utility company in a non-cooperative game and transmits it to the utility company.
  end
end

4. Numerical Results

Here, simulation results of power optimization between multiple relays and DAUs and establishing a communication network topology for an area of Beijing, China are given. It is worth noting that the data used for simulation were collected from historical data in practice. The system has three DAUs, three gateways, and ten relay nodes, as shown in Figure 2. DAUs are allocated at random in a circle with $(116°21.43' \text{ E}, 40°0.73' \text{ N})$ as the center and 3000 m as the radius, and the corresponding gateways are randomly distributed in a circle with $(116°21.43' \text{ E}, 39°57.97' \text{ N})$ as the center and 3000 m as the radius. The relays are ten LTE base stations in two circles with $(116°22.5' \text{ E}, 39°59.28' \text{ N})$, $(116°20.13' \text{ E}, 39°59.28' \text{ N})$ as the center and 1500 m as the radius. The transmitting power of the DAU is 10W, and each relay can allocate transmission power of 20 W. The noise level N_0 is 10^{-9} W, and the parameters are set to be: a = 10,716.91, b = 0.09868, c = 81.91, d = 0.01567, e = 3545, and f = -0.02767. First of all, the simulation results of the DAU leased power ratio α are shown in Figure 3. There are three sets of histograms, and each represents the ratio of leased relay power per DAU. Each set of bars represents, from left to right, the ratio α of leased power from the first relay to the tenth relay. In Figure 4, the ratio sum of relayed power is given. It can be observed that Relay 5, Relay 9, and Relay 10 rented by DAUs account for a large proportion. The purpose of DAUs leasing relay power is to improve communication quality, reduce packet loss rate, and thereby reduce loss cost caused by communication errors. Therefore, the α determined by DAUs is related to the unit price given by the relays. Secondly, only when renting the same amount of power can the communication quality improve as much as possible and the cost be minimized; hence α is related to the distance between DAUs and relays and the distance between relays and gateways.

The decisions of relays depend largely on their relative position in the network topology. Firstly, we analyze the behavior of relays and combine the topology of the network structure and the distance between each relay and DAU as shown in Figure 5. It can be observed that Relay 6, Relay 7, and Relay 8 are in relatively remote locations in the network structure. Therefore, in order to increase its own revenue, relays will tend to two strategies. One is to increase the unit price and reduce the proportion of leased power, such as Relay 1, Relay 3, and Relay 7. The other is to reduce the unit price by attracting DAUs to rent more power, such as Relay 5, Relay 9, and Relay 10.

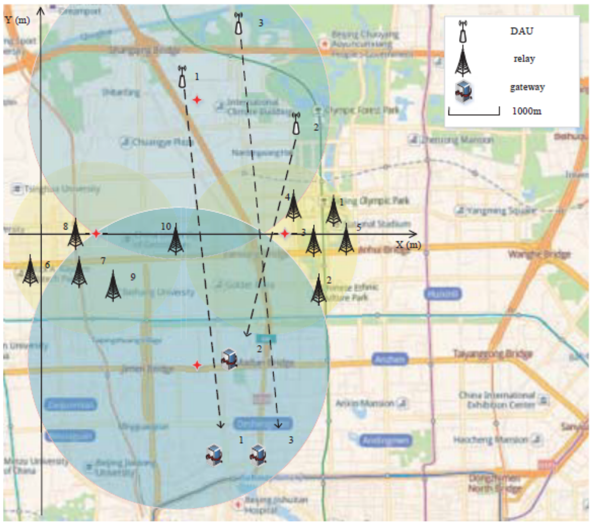

Figure 2. Topology of cooperative relay communication network (red crosses indicate the central points of the circles).

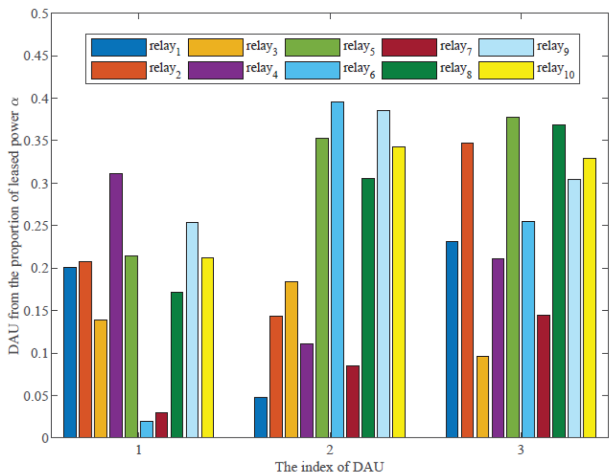

Figure 3. The allocation of relay power to each DAU.

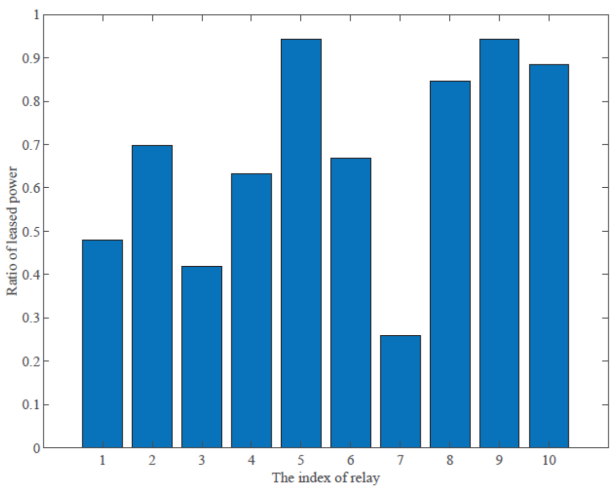

Figure 4. Ratio sum of relayed power.

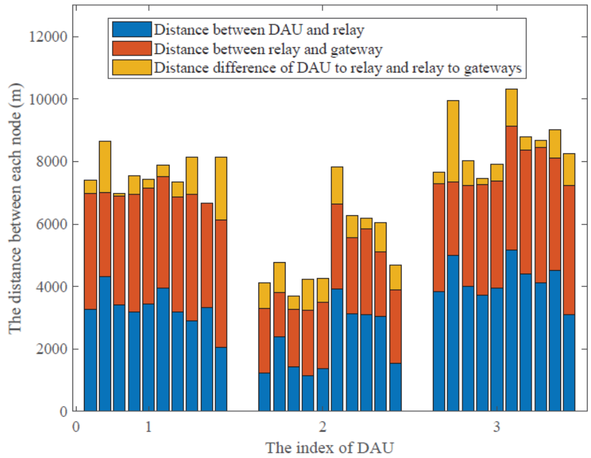

Figure 5. Distance between nodes.

Next, we analyze the behavior of DAUs. Combined with the DAU decision results in Figure 3, the distance between DAUs and relays in Figure 5, and the power unit price provided by the relay in Figure 6, it is observed that DAUs tend to cooperate with the relays at a low unit price and a shorter distance. For example, when the information is transmitted from DAU 1 to Gateway 1, it leases more power ratio to Relay 5, Relay 9, and Relay 10 at a lower unit price and a shorter distance. Moreover, it can be observed from the behavior of DAU 1 that when the unit price and distance are roughly the same, more relays with smaller distances between the DAUs to the relays and the relays to the gateways are selected. When DAU 2 transmits data to Gateway 2, it leases more power ratio to Relay 5, Relay 6, Relay 9, and Relay 10 at a lower unit price. Furthermore, it can be observed from the behavior of DAU 2 that when the unit price and distance are roughly the same, more relays with smaller unit price between the DAUs to the relays and the relays to the gateways are selected. Figure 7 represents the convergence of the algorithm, and the relay revenue converges within five iterations.

Next, two comparison schemes are proposed and simulated on the basis of the previous model.

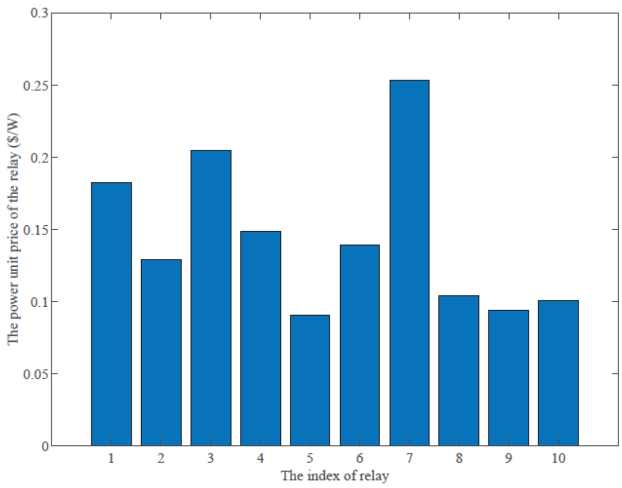

Figure 6. The power unit price of relays.

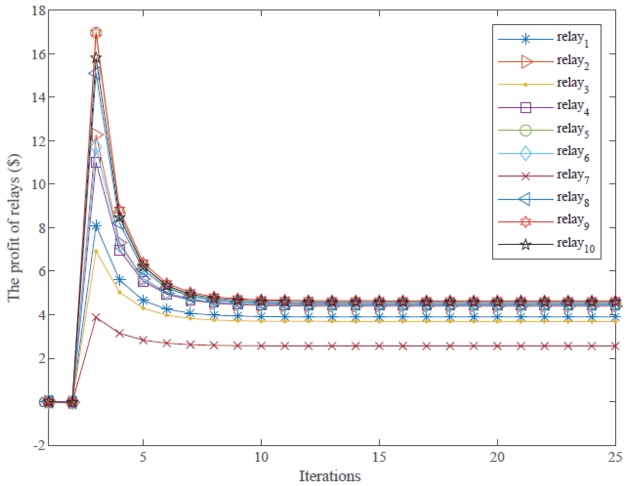

Figure 7. Convergence of the algorithm.

Scheme A: the DAU can only decide whether to request the relay for cooperative transmission but cannot determine the proportion of the leased power. The power ratio available to the DAU is determined by the number of DAUs requesting relay. Meanwhile, the relay can improve its own income by adjusting the unit price of power. For example, if DAU 1 and DAU 2 simultaneously requested Relay 1 for cooperative transmission of forward data, DAU 1 and DAU 2 would obtain 50% of the power, respectively. At this point, the objective function for the utility company is

$$\min Z = \sum_{k=1}^{N} \left(p_a \Phi(P_\mathrm{r}) + \sum_{i=1}^{M} \frac{x_{i,k}}{\sum_{k=1}^{N} x_{i,k}} p u_i \right) \tag{54}$$

where $x_{i,k}$ represents whether DAU k rents Relay i. The revenue function of the relay is denoted as

$$\begin{aligned} \max U_i = & \sum_{k=1}^{N} \frac{x_{i,k}}{\sum_{k=1}^{N} x_{i,k}} p u_i - \\ & \sum_{k=1}^{N} \frac{p\left(1 - \frac{x_{i,k}}{\sum_{k=1} N x_{i,k}}\right)}{N-1} \frac{\ln u_i}{\frac{1}{M-1} \sum_{-i} \ln u_i} u_i. \end{aligned} \tag{55}$$

Through the simulation, the decision results of DAUs are listed in Table 1.

Table 1. DAU decision results under Scheme A.

	DAU 1	**DAU 2**	**DAU 3**
Relay 1	1	1	0
Relay 2	1	0	1
Relay 3	0	1	1
Relay 4	0	1	1
Relay 5	0	1	1
Relay 6	1	0	0
Relay 7	1	0	0
Relay 8	1	0	0
Relay 9	1	0	1
Relay 10	1	1	0

Scheme B: the DAU can cooperate with a relay with the lowest cost, but each relay can only serve one DAU, and the relay can regulate price to avoid multiple DAUs renting the same relay. At this point, the objective function of the utility company is represented as

$$\min Z = \sum_{k=1}^{N} \left(p_a \Phi(P_{\mathrm{r}}) + \sum_{i=1}^{M} x_{i,k} p u_i \right) \tag{56}$$

The revenue function of the relays is represented as

$$\max U_i = \sum_{k=1}^{N} x_{i,k} p u_i - \sum_{k=1}^{N} \frac{p(1 - x_{i,k})}{N-1} \frac{\ln u_i}{\frac{1}{M-1} \sum_{-i} \ln u_i} u_i. \tag{57}$$

Similarly, under the rule conditions of Scheme B, the decision results of DAUs are shown in Table 2. The behavior of DAUs in the two comparison schemes is different from the decision behavior of DAUs. According to the above analysis, Relay 1 and Relay 2 are close to the center of DAU 1 and Gateway 1, and Relay 10 is close to DAU 1 and Gateway 1. The DAUs select Relay 6, Relay 7, Relay 8, and Relay 9 because these relays are positioned at the network's periphery, and they need to reduce the unit price to attract more DAUs for cooperative transmission. In Scheme B, DAU 1 selects Relay 1, Relay 3, and Relay 9. In Table 3, we give the expense of the utility agencies under the proposed scheme and the two comparison schemes mentioned above. Z_1, Z_2, and Z_3, respectively, represent the cost generated by DAU 1, DAU 2, and DAU 3, and Z represents the total cost of the utility company. As shown in Table 3, the utility company cost under the proposed scheme is significantly less than that of the two comparison schemes.

Table 2. DAU decision results under Scheme B.

	DAU 1	**DAU 2**	**DAU 3**
Relay 1	1	0	0
Relay 2	0	0	1
Relay 3	1	0	0
Relay 4	0	1	0
Relay 5	0	1	0
Relay 6	0	1	0
Relay 7	0	1	0
Relay 8	0	0	1
Relay 9	1	0	0
Relay 10	0	0	1

Table 3. The costs of utility companies.

	Model of This Study/$	**Scheme A/$**	**Scheme B/$**
Z_1	555.89	1154.5	1122.5
Z_2	599.05	863.8	1038.5
Z_3	562.22	1125	1401
Z	1717.16	3144.3	3762

5. Conclusions

In this paper, a two-layer cooperative communication network is studied between the utility agency and relays. The utility agency rents the relay to assist the downlink transmission to enhance the reliability of communication and reduce the data transmission cost due to packet loss. Furthermore, the uncertainty of channel gain is considered, and a two-tier game model is established. A distributed robust power regulation algorithm with a continuous convex approximation scheme is presented to obtain the optimal relay power allocation and price. The profit of the relay is improved by adjusting the electricity price, resulting in a reasonable power distribution for cooperative transmission. The comparative simulation results exhibit that the expenses of the utility agencies of the proposed schemes can be reduced by 6% and 21%, respectively. The standard deviations of income values between the relays can be decreased by 40% and 48% respectively.

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