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Joint Relay Selection and Power Allocation for Energy-limited Networks with Cloud Computing

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***Abstract*—We consider a energy-limited network where a source node communicates with a destination node with help of relay node. Appropriate relay node is a good way for solving communication between source and destination and reducing energy consuming. The conventional methods adopt simple and tractable criterion to achieve goal as of tough computation. Cloud computing (CC) technology brings novel ideas that the application of Auto-Regressive and Moving Average ($ARMA$) model in energy-limited networks for our intention. A source selects an appropriate relay node to assisted communication before predicting historical energy information of potential relay nodes through $ARMA$ model. Then, the Lagrange Multiplier is used to optimize the power allocation of nodes to improving network energy. The results show our relay selection algorithm and power allocation method could effectively reduce network energy consumption.**

***Keywords*-$ARMA$ Model; Relay Selection; Power Allocation; Energy-Limited Networks;**

I. Introduction

Nodes in energy-limited networks are confined in terms of batteries. That's because nodes cannot be recharged in process of network operation [1]. In energy-limited networks, such as wireless sensor networks, energy resource is precious and it must be carefully managed in applications [2]. Relay technology is a good choice for improving network energy consumption. In this paper, we consider one case that a source node communicates with a destination node with help of relay node.

So far, many related works focused on cooperation communication in practical networks [3], [4]. Laneman et al. studied classical cooperative diversity protocols under low complexity and analyzed the performance of outage probability under high SNR conditions [3]. On basis of analyzing the performance of two-hop wireless networks with relay node based on AF protocol, specific relay selection scheme application was also proposed in vehicular networks [4]. Power allocation also attracted considerate attention [5], [6]. Si et al. [5] proposed an algorithm for relay selection and power allocation based on the Decode-and-Forward (DF) cooperation protocol. Traditional relay selection and power allocation methods observed channel state, computed estimate value and distributed equally power resources due to technical restriction. The advent of CC technology bring new development and opportunity for technological problem with wireless network [7]. The CC technology provide preeminent platform for application of complex technical models, such as time sequence model [8]. For energy-limited networks, energy is a precious resource and rigorous energy management could maintain stable network operation. Time sequence model could forecast accurately future data at time t according to historical data before time t. Based on the above research, this paper proposes an ARMA model based relay selection and power allocation algorithm to reduces the total energy consumption for energy-limited networks.

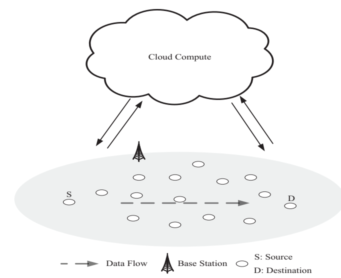

Figure 1. System Model

The remainder of this paper is organized as follows. Section II provides the system model and channel model analysis. Then, the relay selection and power allocation scheme based on the $ARMA$ energy prediction model are described in detail in Section III. In Section IV, the proposed methods in Section III are validated and compared with ordinary relay selection and power allocation algorithms, followed by conclusions in Section V.

II. System Model and Channel Model Analysis

A. System Model

The energy-limited network communication model is shown in Fig. 1. In the network, S is the source node. The relay nodes are in the set R, $R = R_i$, where $i = 1, 2, \cdots, n$ and D is the destination node. The relay nodes in the networks can be pre-deployed as idle nodes that do not need to send information temporarily. When the source S node needs to transmit data, the relay node is selected

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from the relay selection set to relay the information to the destination node D. Note that all nodes and base station in networks could upload their data to Cloud.

B. Channel Model Analysis

1) Data analysis: The transmission process can be divided into two phases. In the first phase, the source node transmits data to all the relay nodes on the orthogonal channel (e.g., TDMA channel). In the second phase, after selecting the relay node, the relay assists the source node to forward data to the destination. The destination node performs signal process for the received data. The signal received by the relay node in the first phase and the signal received by the destination node in the second phase are

$$y_{si} = \sqrt{P_s} h_{si} x + n_{si}, i \in R, \tag{1}$$

$$y_d = \sqrt{P_i} h_{id} x' + n_{id}, i \in R, \tag{2}$$

where x and x' are the transmitted data normalized by the power of the source node and the relay node, $E[|x|^2] = E[|x'|^2] = 1$. P_s and P_i are the transmission powers of the source node and the relay node R_i, respectively. h_{si} is the channel fading coefficients between the source node and the relay R_i while h_{id} is the coefficients between the relay i and the destination node. They are both independent, cyclically symmetric complex Gaussian random variables with a mean of 0, and the variances are σ_{si}^2 and σ_{id}^2, respectively. n_{si} and n_{id} are the independent zero-means additive Gaussian white noises with a variance of σ^2 of the corresponding channel.

Using the AF protocol, gain amplification and receiving signals at relay node are

$$G = \frac{1}{\sqrt{P_i |h_{si}|^2 + \sigma_{id}^2}}, \tag{3}$$

$$x' = G y_{si}, \tag{4}$$

Then, the signal received at the destination node becomes

$$\begin{aligned} y_d &= \sqrt{P_i} h_{id} x' + n_{id} \\ &= \sqrt{\frac{P_s P_i}{P_s |h_{si}|^2 + \sigma_{id}^2}} h_{si} h_{id} x + \sqrt{\frac{P_i}{P_i |h_{si}|^2 + \sigma_{id}^2}} h_{id} n_{si} \\ &= +n_{id}, i \in R. \end{aligned} \tag{5}$$

The signal to noise ratio of the signal received by the destination node is

$$\gamma = \frac{\gamma_{si}\gamma_{id}}{\gamma_{si}\gamma_{id} + 1}, i \in R \tag{6}$$

where $\gamma_{si} = P_s |h_{si}|^2 / \sigma^2$, $\gamma_{id} = P_i |h_{id}|^2 / \sigma^2$. For ease of calculation, we assume that the channel variance $\sigma^2 = 1$.

2) ARMA Model: $ARMA$ model is suitable for short-correlation prediction and has a low algorithm complexity. It is highly accurate when used to predict short-correlation flows and is suitable for online prediction or energy-constrained scenarios. The $ARMA$ model can effectively analyze the data sequence correlation for stationary data sequences in application [9].

Let $\{\xi_t\}$ be white noise with a mean of 0 and a variance of σ^2. The real coefficient polynomials $A(Z)$ and $B(Z)$ have no common root, satisfying $b_0 = 1$, $a_p b_q \neq 0$ and

$$A(z) = 1 - \sum_{j=1}^{p} a_j z^j \neq 0, |z| \leq 1, \tag{7}$$

$$B(z) = \sum_{j=0}^{q} b_j z^j \neq 0, |z| < 1, \tag{8}$$

The difference equation is achieved [8]

$$X_t = \sum_{j}^{p} a_j X_{t-j} + \sum_{j=0}^{q} b_j \xi_{t-j}, t \in Z, \tag{9}$$

The eq.(9) is an $ARMA$ model which satisfies the stationary sequence, abbreviated as $ARMA(p,q)$ model. For the collected data sequence, it is assumed to be $s' = [x_0', x_1', \cdots, x_n']$, and is logarithmically processed using a method of sequence smoothing to obtain $s = [x_0, x_1, \cdots, x_n]$. The stability of s is considered, and the autocorrelation function and partial correlation function of s are calculated. According to the tailing phenomenon presented, it is determined as an $ARMA$ sequence.

The order of $ARMA$ is determined using the AIC order method [8]. The AIC criterion function is given by

$$AIC = -2L(\widehat{\beta}) + 2k, \tag{10}$$

where $\widehat{\beta}$ is the maximum likelihood estimate of the parameter, $L(\cdot)$ is the likelihood function, and k is the number of independent parameters.

When the sample length n is large enough, the likelihood function of the $ARMA(p,q)$ model is approximately

$$L(\widehat{\beta}) = -\frac{n}{2} lg 2\pi - \frac{n}{2} lg \widehat{\sigma}^2 - \frac{S(\widehat{\beta})}{2\widehat{\sigma}^2}, \tag{11}$$

where $S(\widehat{\beta}) = n\widehat{\sigma}^2$ and $\widehat{\beta} = (\widehat{\varphi}, \theta)^T = (\varphi_1, \varphi_2, \varphi_3, \cdots, \varphi_p, \theta_1, \theta_2, \theta_3, \cdots, \theta_q)^T$.

Substituting eq.(11) into eq.(10), given that n is sufficiently large, the minimum information criterion for $ARMA(p,q)$ model fitting is equivalent to minimizing the following equation.

$$AIC(p,q) = n lg \widehat{\sigma}^2 + 2(p + q + 1), \tag{12}$$

Through analysis, we use $ARMA(2,1)$ to make predictions. The model is

$$(1 - \varphi_1 B - \varphi_2 B^2) x_i = \theta(B) a_i, \tag{13}$$

where B is the post-shift operator, a_i is the white noise and $\varphi_1, \varphi_2, \theta_1, \sigma^2$ are the estimated parameters. The least squares estimation method is used to solve the parameters

$\widehat{\varphi}_1, \widehat{\varphi}_2, \widehat{\theta}_1, \widehat{\sigma}^2$. For the stability judgment of the time sequence, according to the stability conditions $\widehat{\varphi}_1 + \widehat{\varphi}_2 < 1, \widehat{\varphi}_2 - \widehat{\varphi}_1 < 1$ and $|\widehat{\varphi}_2| < 1$, it is determined as a stationary sequence, and the $ARMA$ model is obtained as the following equation.

$$x_t = \widehat{\varphi}_1 x_{t-1} + \widehat{\varphi}_2 x_{t-2} + a_t - \widehat{\theta}_1 a_{t-1}, \tag{14}$$

Then use the inverse function method to get a further expression of the $ARMA$ prediction model:

$$\widehat{x}_t(1) = \sum_{j=1}^{m} I_j x_{t+1-j}, \tag{15}$$

where I_j is the $ARMA$ inverse function, and m is the number of observations before x_t, which can be determined by the prediction accuracy. The corresponding multiple forecasting model is

$$\widehat{x}_t(l) = \widehat{\varphi}_1 \widehat{x}_t(l-1) + \widehat{\varphi}_2 \widehat{x}_t(l-2). \tag{16}$$

III. Design of Relay-assisted Scheme

A. Relay Selection Algorithm

The candidate relay set R is set, and all $R_i \in R, i \in \{1, 2, \cdots, N\}$ are arranged in descending order according to the $ARMA$ prediction energy value. In the single relay node cooperative communication process, the source node S selects the relay node with the largest energy value to carry out relay communication. This algorithm is described by

$$R_S = arg \max_{R_i \in \Re, i \in \{1,2,\cdots,N\}} E_{R_i}. \tag{17}$$

where E_{R_i} is the predicted energy value of relay R_i.

According to the above description, the relay-assisted selection algorithm is given by $Algorithm 1$. This algorithm based on $ARMA$ guarantees that the relay data is always forwarded by the relay node with the largest energy value. CC technology ensures compute capability for $ARMA$ and further reduces the energy exhaustion or death when the low energy selected node relays data.

B. Power Allocation Algorithm

On the basis of the above-mentioned in Section III-A, reasonable power allocation is another important measure to improve energy performance of networks. Based on the link channel state information, this paper optimizes the power of the nodes in the energy-limited networks. The specific condition is given by

$$\begin{aligned} &\min_{R_i \in \Re} P = P_S + P_{SR_i} \\ &s.t. \gamma \geq \hbar \end{aligned} \tag{18}$$

where P is the total power of the relay network, P_{SR_i} is the power of the selected relay R_i, γ is the SNR of the destination node, and $\hbar$ is the minimum SNR that satisfies energy performance of networks.

Combining eq.s (6), (17) and (18), to solve the convex optimization problem in eq. (18), that is, to optimize the variables P_S and P_{SR_i} in the eq. (19), the Lagrange

Algorithm 1 Pseudo-Code of the single-relay selection algorithm

```
if S = 1 then
    S transmits messages via Relay;
    for i = 1 to n do
        Record the historical energy information, E_{R_i}, in the candidate relay set ℜ at time t;
        x_i ← E_{R_i};
        Ψ ← x_i;
        Upload to cloud with Ψ;
        Running ARMA prediction model according to SectionII-B2 by CC;
        L ← ARMA(ℜ) at time t + 1;
    end for
    U = sort(L);
    Q = fliplr(U);
    n* = Q(1).
    n* is denoted as the relay-assisted node.
else
    S communicates directly with D.
end if
```

Multiplier method can be used to find the optimal power expression that satisfies equation (18) is

$$\begin{aligned} P_S &= \frac{\sqrt{\hbar(\hbar+1)}|h_{si}| + \hbar|h_{id}|}{|h_{id}||h_{si}|^2} \\ P_{SR_i} &= \frac{\hbar|h_{si}| + \sqrt{\hbar(\hbar+1)}|h_{id}|}{|h_{id}|^2|h_{si}|} \end{aligned} \tag{19}$$

At this time, the minimum total power consumption of the network system in the case of optimal relay is:

$$P = \frac{(\sqrt{\hbar}|h_{si}| + \sqrt{\hbar+1}|h_{id}|)^2 - |h_{id}|^2}{|h_{si}|^2|h_{id}|^2}. \tag{20}$$

From eq.s (19) and (20), it can be seen that when the relay node R_i is determined by the $ARMA(2,1)$ energy prediction model under the model shown in Fig.1, the total energy consumption of the network is minimal when power is distributed between the source and the relay by the method of (19).

IV. Simulation Results and Analysis

This section carries out a simulation analysis of the determination of the $ARMA$ energy prediction model. When the relay node adopts the AF protocol, performance comparison is made between the selected $ARMA$ energy prediction model and the traditional random relay selection algorithm in terms of network energy.

This paper uses random values to verify the energy data required by the model during the simulation process. After repeating the $ARMA$ energy prediction model 10 times, 10 groups of experimental data were randomly generated in this process. Through the analysis process in Section II-B2, the comparison of the $ARMA(2,1)$ and $ARMA(2,2)$ energy model is shown in Fig. 2.

From Fig. 2, the $ARMA(2,1)$ and the $ARMA(2,2)$ energy prediction models have errors compared to the

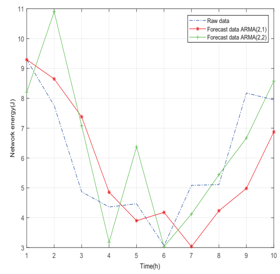
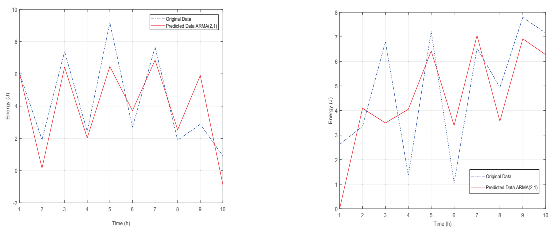


Figure 2. The comparison of network energy between two methods



(a) One Step Prediction

(b) Two Step Prediction

Figure 3. The comparison of network energy with One and Two step prediction

original data, because the simulation is affected by the built scene model and the impact of selected data. However, compared with the $ARMA(2,2)$ energy prediction model, the $ARMA(2,1)$ energy prediction model can better reflect the changing state of the original data. For the deterministic $ARMA(2,1)$ energy prediction model, comparing this model with one-step prediction and two-step prediction, the results are shown in Fig. 3.

From Fig. 3, we can see that when the $ARMA(2,1)$ energy prediction model adopts one-step prediction, it can have better prediction performance. Therefore, in this simulation process, one-step $ARMA(2,1)$ energy prediction model is selected to perform Predictive analysis of data.

The comparison of network energy between the random selection method and the proposed method is shown in Fig. 4 when the historical values are randomly generated. From Fig. 4, we can see that deploying the distribution network using the proposed scheme can more effectively use the energy of the network nodes, meanwhile reduce the network energy consumption and extend the network life cycle.

V. Conclusions

A joint relay selection algorithm and a power allocation algorithm are proposed in the energy-limited networks with CC. The relay selection algorithm using $ARMA$ energy prediction model can effectively select relay node. On this basis, an optimal power allocation solution is obtained through the Lagrangian multiplier method. Simulation results indicate that our method can improve the energy consumption of the network.

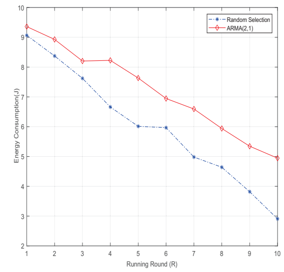


Figure 4. The comparison of network energy between two methods

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