Energy-aware Routing Algorithm Based on Combinatorial Optimization Theory

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Abstract **— In allusion to the conflict between transmission power consumption and residual energy of node in traditional OLSR algorithm, an energy-aware routing algorithm based on combinatorial optimization theory (EW-OLSR) is proposed in the article. Firstly, the mathematical model for node energy consumption is established according to transmission power consumption and residual energy of node, and is regarded as the objective function for routing; then, ARIMA-LSSVM combinatorial prediction model is introduced therein for calculating the residual energy of node, and data transmission route is determined according to minimum energy consumption routing; finally, simulation experiment is adopted to test algorithm performance.**

Keywords - mobile Ad-Hoc network; olsr algorithm; auto regressive integrated moving average; least squares support vector machine

I. INTRODUCTION

MANET (Mobile Ad-hoc network) is a wireless network without the need of infrastructure, and compared with cellular mobile network, MANET can establish wireless network for communication at any time and any place without the need of any central control equipment, so MANET has been successfully applied to such fields as rescue and relief, resource exploration and military communication. Due to the adoption of multipoint relay mechanism for reducing the flooding range of the control packet, OLSR (Optimized Link State Routing) algorithm, as an important MANET routing algorithm, has good performance in multi-node or dense node network. In practical application, OLSR protocol has many defects, such as large energy consumption and severe resource wasting. Therefore, the key research content in MANENT is always to design OLSR protocol with excellent performance [1].

In order to conquer the deficiency of OLSR algorithm, scholars and researcher in China have carried out a lot of in-depth researches and accordingly proposed some improved OLSR algorithms. At present, the improvements for OLSR algorithm mainly involve two aspects: on the one hand, routing energy consumption shall be maximally reduced and the route needing minimum energy consumption shall be selected for data packet transmission; on the other hand, the node with highest residual energy shall be selected as the routing node according to maximum-minimum routing path. However, the above improvements also have corresponding deficiencies, such rapid energy consumption and short network survival time [2].

Additionally, OLSR algorithm needs to obtain the residual energy status of the node itself, some scholars adopt ARIMA (Auto Regressive Integrated Moving Average) model for energy consumption prediction in order to obtain the residual energy value of the node, but ARIMA is based on linearity theory for modelling, thus to be difficult to accurately describe the time-dependent nature of energy consumption of the node and accordingly make this model have certain limitation.

In order to reduce the energy consumption of the node and improve success rate of data transmission as well as take advantages of ARMIMA and LSSVM (Least Squares Support Vector Machine), an energy-aware routing algorithm based on combinatorial optimization theory (EW-OLSR) is proposed in the article. Firstly, the mathematical model for node energy consumption is established according to transmission power consumption and residual energy of node, and is regarded as the objective function for routing; then, ARIMA-LSSVM combinatorial prediction model is introduced therein for calculating the residual energy of node, and data transmission route is determined according to minimum energy consumption routing; finally, simulation experiment is adopted to test algorithm performance [3].

II. MATHEMATICAL MODEL FOR ENERGY CONSUMPTION

To simplify the model, the following assumptions are made before the mathematical model for the energy consumption of OLSR algorithm is established [4]:

(1) Node is supplemented with any energy and is always in any of the three energy consumption modes, namely data packet transmission, data packet receiving and idle status.

(2) Each node has its fixed transmission range.

In the initial period, EW-OLSR algorithm selects the route with minimum transmission power consumption in order to reduce communication overhead; at the later period, EW-OLSR algorithm preferentially selects the node with high residual energy for routing in order to maintain the balanced energy consumption of the network. The design objective of EW-OLSR is to select the route with minimum objective function. R denotes a route between the source node and the destination node, and the objective function is defined as [5]:

$$W_R(t) = \sum_{i \in R} W_{R\_i}(t) \tag{1}$$

$$\begin{aligned} W_{R\_i}(t) = P_{t\_i} + K_1(E_{full\_i} - R_i(t)) / E_{full\_i} \\ + K_2(E_{full\_i} - R_i(t)) / E_{\max} \end{aligned} \tag{2}$$

III. ENERGY CONSUMPTION PREDICTION OF ARIMA-LSSVM

During MANET operation process, due to the comprehensive influence of various factors, the energy consumption of node has nonlinearity and time-dependent nature. Therefore, ARIMA with strong linear prediction ability and LSSVM with excellent nonlinear prediction ability are combined for the modeling and prediction of energy consumption of node so as to accurately capture node energy change condition [6].

A. *ARIMA Algorithm*

The basic thought of ARIMA is as follows: firstly, *d*-order differential operation is carried out for instable time series *Z*; then, ARMA (*p*, *q*) model is established for the differential stable series $(1\text{-}B)^d Z$ obtained thereby. Theoretically, the general form of ARMA (*p*, *d*, *q*) is as follows:

$$\begin{aligned} (1 - \varphi_1 B - \ldots - \varphi_p B^p)(1 - B)^d Z_t \\ = \theta_0 + (1 - \theta_1 B - \ldots - \theta_q B^q)\varepsilon_t \end{aligned} \tag{3}$$

In the formula, *B* is lag operator; B^k is the k-th lag operator; ε_t is the white noise with variance of σ^2; Φ_i (i=1, 2,…, p) and θ_j (j=1, 2,…q) are the unknown parameters of the model, *p* and *q* are the orders of the model [7].

B. *ARIMA Modeling Steps are As Follows:*

(1) Carry out unit root test for original data; if the stability condition cannot be met, convert the original data into stable data through differential operation and establish ARMA (*p*, *q*) model.

(2) Preliminarily identify the possible forms of the model according to autocorrelation coefficient and partial correlation coefficient, and then select an optimum model according to such order determinations criterions as AIC and SC [8].

(3) Adopt nonlinear least square method to estimate model parameters and meanwhile check whether the significance of model parameters and the model validity as well as the residual error series are white noise or not. If the model passes the verification, then the model setting can be judged to be correct; or else, the model form must be determined again till the correct model form is obtained.

(4) Use ARMA (*p*, *d*, *q*) model established thereby for prediction.

C. *LSSVM Algorithm*

LSSVM adopts nonlinear mapping function $\Phi(\cdot)$ to map the training samples $\{(x_i, y_i)\}$ (i=1,2,…,n) to the high-dimension characteristic space and then carries out linear regression, namely:

$$f(x) = w^T \varphi(x) + b \tag{4}$$

In the formula, ω is weight vector and *b* is offset quantity.

According to structural risk minimization principle, formula (4) can be converted as:

$$\begin{aligned} & \min \|w\|^2 + \frac{1}{2}\gamma \sum_{i=1}^{n} \zeta_i^2 \\ & s.t. \\ & y_i - w^T \varphi(x) + b = e_i \end{aligned} \tag{5}$$

In the formula, γ is regularization parameter; e_i is error.

Then, Lagrangian multiplier is introduced therein to convert it into duality optimization problem, namely:

$$\begin{aligned} L(w,b,\zeta,\alpha) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{i=1}^{n} \zeta_i^2 + \\ \sum_{i=1}^{n} \alpha_i (w^T \varphi(x_i) - b + \xi_i - y_i) \end{aligned} \tag{6}$$

In the formula, α_i is Lagrangian multiplier.

The optimization condition is as shown in the following formula:

$$\frac{\partial L}{\partial w} = 0, \frac{\partial L}{\partial b} = 0, \frac{\partial L}{\partial \xi_i} = 0, \frac{\partial L}{\partial \alpha_i} = 0$$

Then, the following formula can be obtained:

$$\begin{aligned} & w = \sum_{i=1}^{n} \alpha_i \varphi(x_i), \sum_{i=1}^{n} \alpha_i = 0, \alpha_i = c\xi_i, \\ & w\varphi(x_i) + b + \xi_i - y_i = 0 \end{aligned} \tag{7}$$

According to Mercer condition, the kernel function is defined as $K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$, and LSSVM regression model is as follows:

$$f(x) = \sum_{i=1}^{n} \alpha_i K(x_i, x_j) + b \tag{8}$$

D. *Energy Consumption Combination Prediction of ARIMA-LSSVM*

(1) Adopt ARIMA to establish corresponding model for the energy consumption of node in order to predict the linear variation rule thereof, wherein the residual error between actual value and predicted value includes the nonlinear change characteristics of the energy consumption of node.

(2) Adopt LSSVM for the linear modeling and prediction for the residual error series in order to obtain the nonlinear prediction result of energy consumption, wherein the radial basis kernel function is selected as LSSVM kernel function.

(3) Combine the prediction results of ARIMA and LSSVM to obtain the prediction result of the energy consumption of node.

(4) Put the predicted value of the energy consumption of node to formula (9) to obtain the predicted value of the residual energy of node through recursion.

$$R_i(t) = R_i(t-1) - E_i(t) \quad (9)$$

In the formula, E_i(t) and R_i(t) are respectively the predicted values of the energy consumption and the residual energy of node *I* within the *t*-th cycle [9].

The process of energy consumption prediction of ARIMA-LSSVM is as shown in Fig. 1.

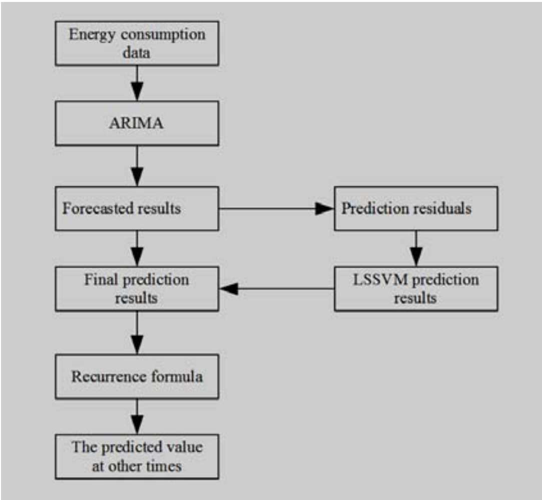

Figure 1. ARIMA-LSSVM working process

E. *EW-OLSR Algorithm*

Based on OLSR algorithm, the prediction mechanism of residual energy of node is introduced in EW-OLSR algorithm and is mainly composed of ARIMA-LSSVM prediction module, energy consumption management module and routing list calculation module. The working steps of EW-OLSR algorithm are as follows:

(1) Statistically collect data packet transmission power consumption, primary energy and present energy of the node and broadcast them to other nodes through TC message.

(2) Transfer present energy to ARIMA-LSSVM prediction module to obtain the residual energy of node, broadcast the residual energy to other nodes, and store it in energy consumption management module.

(3) Energy consumption management module adopts the data received from other nodes and regarding the primary energy, the present energy and the transmission power consumption for energy consumption calculation in order to update energy consumption data.

(4) In routing list calculation module, replace hop count by energy consumption and select the route with minimum overhead [10-11].

In conclusion, the working principle of EW-OLSR algorithm is as shown in Fig. 2.

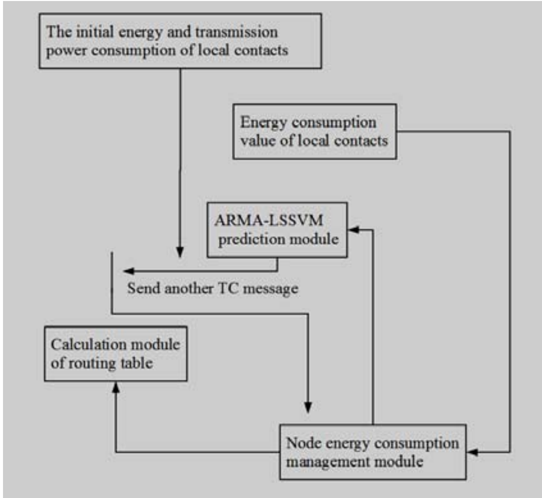

Figure 2. Working principle of EW-OLSR algorithm

IV. SIMULATION EXPERIMENT

A. *Simulation Environment*

In order to verify the validity of EW-OLSR algorithm, Matlab 2012 simulation tools are used in the computer (Dell E520, 4GB memory, Windows XP operating system) for testing experiment. In order to strengthen the persuasion of EW-OLSR algorithm, standard OLSR algorithm and the improved OLSR algorithm mentioned in literature are selected for the contrast experiment, wherein the minimum residual energy of node, the average residual energy of node, the transmission delay, the grouping arrival rate and other relevant performance indexes are adopted to evaluate the advantages and disadvantages of the algorithm. The network parameters of the simulation experiment are as shown in Table 1.

TABLE I SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
Region Size	1000m×1000m	Total Nodes	50
Data Packet Size	512Bytes	Motion Model	Random
Node Movement Speed	2m/s~15m/s	Data Packet	40kbps
Simulation Time	1000s		

B. *Result and Analysis*

1) *Comparison of minimum residual energy of nodes*

The minimum residual energy change curves of nodes in EW-OLSR algorithm and other OLSR algorithms are as shown in Fig. 3. According to Fig. 3, the minimum residual energy of nodes in all routing algorithms tends to be increased along with the increase of node movement speed, and under the same condition, EW-OLSR algorithm can better balance node usage rate due to the introduction of energy prediction mechanism, thus to prevent some nodes from being excessively used and effectively maintain the balanced network load as well as make the nodes have highest minimum residual energy [12].

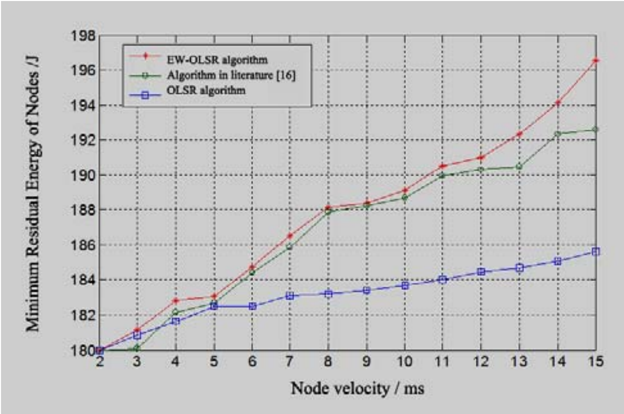

Figure 3. Comparison of minimum residual energy of nodes in different algorithms

2) Average residual energy of node

The average residual energy change curves of nodes in EW-OLSR algorithm and other OLSR algorithms are as shown in Fig. 4. According to Fig. 4, the average residual energy of nodes in all routing algorithms tends to be increased along with the increase of node movement speed, and under the same condition, relatively to the comparison algorithms, EW-OLSR algorithm can reduce the energy consumption of network and improve the average residual energy of node as well as effectively protect the energy utilization of network.

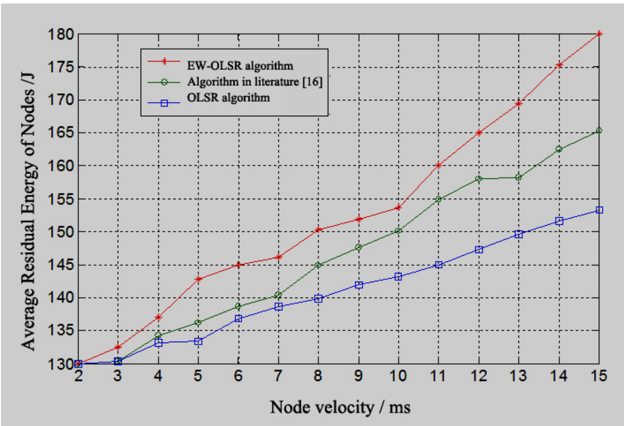

Figure 4. Average residual energy of nodes in different algorithms

3) Transmission delay comparison

The transmission delay change curves of EW-OLSR algorithm and other OLSR algorithms are as shown in Fig. 5. According to Fig. 5, the transmission delay of all routing algorithms is increased along with the increase of the node movement speed. Specifically, when the movement speed is relatively low, the transmission delay of these routing algorithms is only slightly different from each other; when the movement speed has certain increase, compared with comparison algorithms, EW-OLSR algorithm has shorter transmission delay, thus to present obvious advantages.

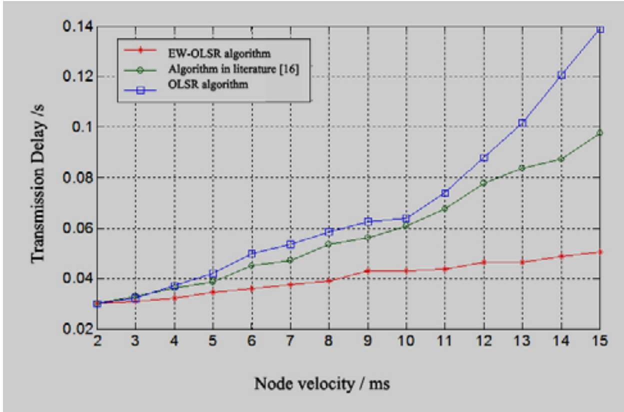

Figure 5. Comparison of transmission delay of different algorithms

4) Grouping arrival rate

The grouping arrival rate change curves of EW-OLSR algorithm and other OLSR algorithms are as shown in Fig. 6. According to Fig. 6, the grouping arrival rates of all routing algorithms are reduced along with the increase of node movement speed; specifically, when the node has relatively low movement speed, the grouping arrival rates of these routing algorithms only have slight difference; when the node has relatively large movement speed, the grouping arrival rates of these routing algorithms have obvious difference, because the instability of the data transmission link is increased along with the increase of movement speed. Under the same movement speed, EW-OLSR algorithm has higher grouping arrival rate and can improve the success rate of data transmission and meanwhile significantly improve the communication quality of wireless network.

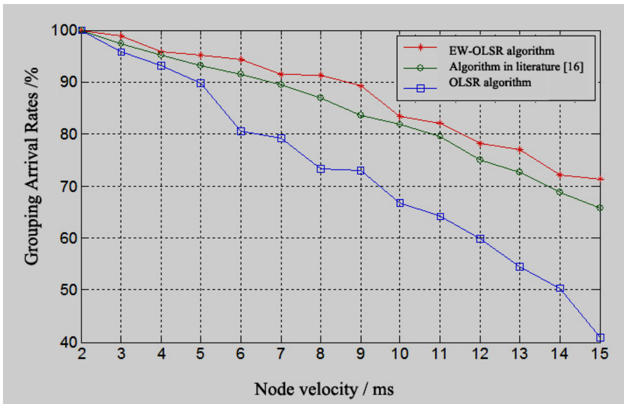

Figure 6. Comparison of grouping arrival rates of different algorithms

V. CONCLUSIONS CONFLICT OF INTEREST ACKNOWLEDGMENT

In order to improve the communication quality of MANET, the energy-aware routing algorithm based on combinatorial optimization theory is proposed in the article, and RIMA-LSSVM is introduced therein to predict the residual energy of node, and hop count is replaced by the energy consumption and the residual energy of the node. The simulation experiment result shows that EW-OLSR algorithm can not only reduce the energy consumption of network, but also ensure the load balance of nodes. Compared with other OLSR algorithms, EW-OLSR algorithm has obvious advantages.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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