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Short-Term Prediction of Cloud Computing Virtual Resource Load Based on Openstack

Mingchao Wang*

College of Mechanical Electronic and Information Engineering, Wuxi Vocational Institute of Arts & Technology, Yixing 214206, China

The allocation of the cloud computing virtual resource load is vulnerable to cloud computing network transmission channel load ambiguity resulting in the poor configuration of this load. In order to improve the efficiency of load allocation, a link robustness prediction algorithm for cloud computing virtual resource load allocation based on OpenStack is proposed. The link routing node channel model of wireless sensor network is constructed, the spread spectrum processing of the data forwarding channel is carried out by wireless random sequence scheduling technology, the modulation component of link robustness prediction is calculated, and the channel transmission delay and multi-grained adaptive weighting value are obtained by the link routing node adaptive modulation method. The simulation results show that the short-term prediction of link robustness using this method for load allocation in the cloud has high accuracy, strong anti-interference, low energy consumption and enhanced node activity.

Keywords: OpenStack, Cloud Computing, Virtual Resources, Load, Short-term Forecast.

1. INTRODUCTION

With the development of network communication technology, the use of wireless sensor networks for data transmission and scheduling has become an important direction of network communication development in the future (Hu et al., 2013). At present, wireless sensor networks are widely used in various domains such as national defense, intelligent agriculture, environmental governance, water quality monitoring, air pollution early warning, health care, smart home, urban traffic and safety monitoring, among others. With the continuous development and maturity of sensor network technology, as well as the popularity of the Internet of Things (IoT), wireless sensor networks will become increasingly ubiquitous. Sensor nodes generally include common nodes and sink nodes, and observers usually distribute a large number of sensor nodes in the monitoring area. According to the pre-set topology or random composition of the network, the common node collects the sensing data and sends the data to the sink node through multiple hops. Similarly, the sink node sends the information to each sensor node through multiple hops. The sensor nodes of a wireless sensor network are deployed in various environments; they are numerous and their location is changed according to need, so it is difficult to establish the topology between nodes in advance. Therefore, a wireless sensor network should have a self-organization function. Each sensor node spontaneously forms a dynamic network topology through a routing protocol. The main task of a wireless sensor network is to collect environmental data. All an observer has to do is collect, manage and analyze the sensing data, and not be concerned with which node collects the data and how it is transmitted. The collected information is transmitted through sensors to the “cloud” information base for storage and sharing, and the whole management process is strengthened to eliminate regulatory blind spots, so as to improve environmental governance. Wireless sensor networks positioned in forested and in coastal areas can collect massive amounts of data in real time, and then combine with the powerful processing ability of the back-end cloud

*Corresponding Author e-mail: noweisky@126.com

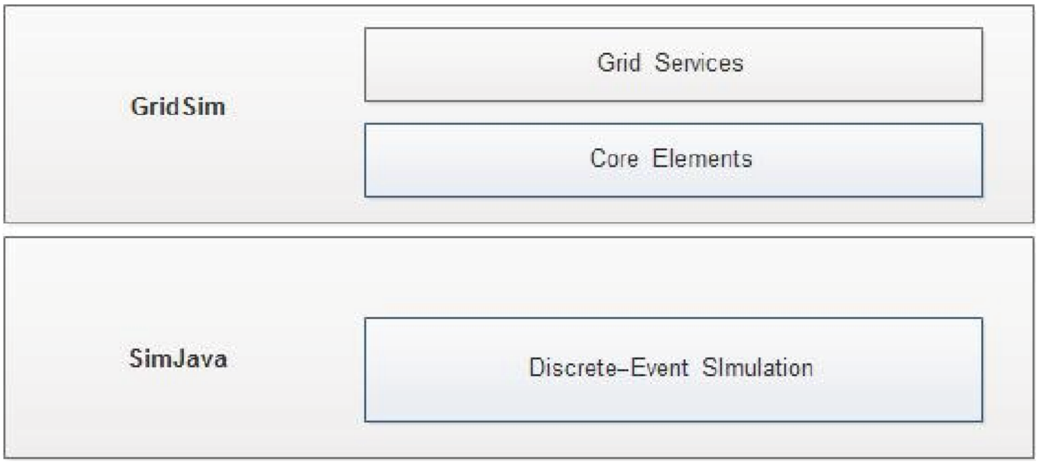

Figure 1 Core Engine Layer.

computer platform to store the data as a resource on the cloud platform (Soh et al., 2019; Aditi and Arvind, 2019; Janzene, 2019).

A wireless sensor network is based on the link network design and forwarding control design of a wireless sensor, combined with link-balanced scheduling to optimize networking and improve the transmission ability of the network. It is important to study the method for short-term prediction of cloud computing virtual resource load in order to optimize the transmission performance and communication ability of the network. In this method, the dynamic channel allocation algorithm CSQCA (channel switching queue-based channel location) is applied, combined with the key shift keying (PSK) method to control the link robustness in cloud computing virtual resource load allocation (Huang et al., 2013). However, the channel equalization of the above method is not effective for link prediction, and the random forwarding performance of the routing node is not good. Hence, a link robustness prediction algorithm based on OpenStack in cloud computing virtual resource load allocation is proposed to optimize the short-term prediction of cloud computing virtual resource load. Finally, the experimental test analysis is carried out to establish the validity conclusion (Zheng et al., 2013).

2. BASIC DEFINITIONS

In order to achieve robust prediction in cloud computing virtual resource load allocation, we first construct the link forwarding routing node channel model of the wireless sensor network (Zhao et al., 2014).

From top to bottom, a wireless sensor network has several layers of protocols: physical layer, data link layer, network layer, transmission layer and application layer. These protocols, together with power management, security management and task management platforms, can achieve network time synchronization, node positioning, transmission control, path, channel access and topology generation.

The physical layer is responsible for signal modulation and data transmission, generally using radio, infrared, light wave and other transmission media.

The data link layer is responsible for the implementation of point-to-point and point-to-multipoint communication by the media access protocol, and an error control checks whether there is any error in the communication between the source node and the target node.

The network layer realizes the discovery and maintenance function of the route in the network. Most nodes in the network need to transmit the data to the aggregation node in the form of multi-hop forwarding with the help of intermediate nodes, requiring multiple routing protocols in the network layer.

The transmission layer controls the data flow in the network, and sends the data collected by the convergence node to the Internet through the communication satellite and wireless network.

The application layer implements specific functions for specific applications, such as data prediction, time synchronization and node positioning. The node has the ability of an ad hoc network.

After deployment, the wireless sensor node forms a communication network with other nodes in a self-organized way through the pre-set communication protocol in the node. Data can be forwarded in the network, and the data can be forwarded to the aggregation node in a multi-hop way. After some nodes die, the network topology can be adjusted automatically. The characteristics of large-scale and dense deployment of nodes often make the monitoring data of adjacent nodes have strong spatial correlation. Spatial correlation refers to the continuity of several physical phenomena monitored by nodes in space, which leads to the similarity of the change rules of the data or data collected by adjacent nodes. Some physical phenomena of node monitoring have continuity or continuity in space, which results in similar or identical data or data change rules obtained by node continuous sampling, known as the ‘time correlation’ of data. If the prediction error is less than the given threshold value, the prediction value is used to replace the monitoring value at the convergence node to save the information transmission process and reduce the data transmission in WSNs.

We use the random link forwarding protocol model to construct the transmission structure model of the wireless sensor network. Set $S = \{s_1, s_2, \ldots, s_k\}$ represents the

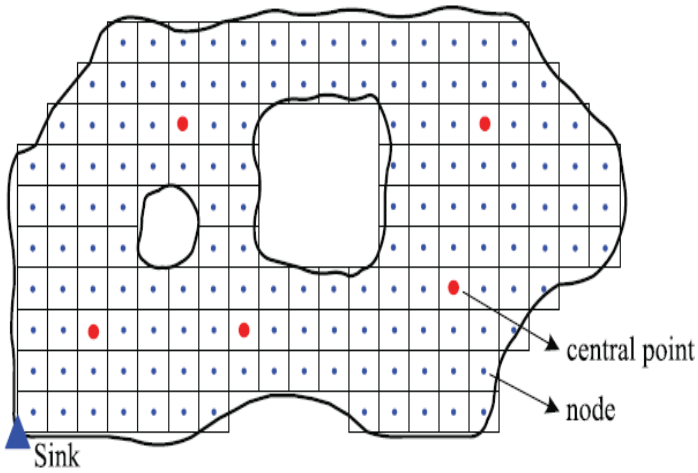

Figure 2 Network Link Forwarding and Node Deployment Model.

node distribution set of the wireless sensor network; Vector $\boldsymbol{x} = [x_1\ x_2 \ldots x_k]$ represents the packet length of the network node, x_i represents the symbol distribution selected by the cloud computing virtual resource load allocation channel, and $i \in S$ represents the similarity characteristics of the channel selection policy $r_i(\boldsymbol{x})$ in the cloud computing virtual resource load allocation. The node coverage area a of the wireless sensor network is divided into $w \times 1\frac{\sqrt{2}}{2}R_c \times \frac{\sqrt{2}}{2}R_c$ square regions. The geographical location of the nodes in V_c is calculated. Each sensor node knows its own geographical location. Sink divides the entire network area into C clusters. The network link forwarding and node deployment model are obtained as shown in Figure 2.

3. LINK FORWARDING CHANNEL MODEL AND SPREAD SPECTRUM ANALYSIS IN WIRELESS SENSOR NETWORKS

In a wireless sensor network, the energy consumed by data transmission accounts for the main energy consumption of a node. If the node sends all the collected monitoring data to the aggregation node, it not only consumes more energy, but also reduces the communication efficiency. Using data prediction technology to reduce the amount of data transmission in WSNs network is an effective way to solve this problem. In the large-scale and densely deployed wireless sensor networks, the data collected by the nodes has a strong spatiotemporal correlation, which makes it possible to use spatiotemporal correlation for accurate data prediction, so as to reduce the amount of data transmission, reduce the energy consumption of data transmission, and extend the network life. According to the characteristics of the monitoring data, the data prediction technology adopts the appropriate data prediction algorithm to preprocess the monitoring data in the sensor node, analyzes the change rule of the data and the change relationship between the data, and forecasts the current data value according to the change trend of the data. This not only reduces the amount of data transmitted in the network, but also prevents any communication conflict in the channel. Hence, the efficiency of data transmission is improved, the energy consumption of node communication is reduced, and the life cycle of the network is extended.

A wireless sensor network is a multi-hop self-organized network system formed by wireless communication. The security and robustness of its nodes, extension structure and other network elements are always fluctuating, so the security of the whole network is a dynamic variable. Assuming that the network is free from external interference and that all components are operating well, the security situation of the whole network is absolutely safe. However, if not every component of the network is operating normally, then the network is absolutely unsafe. Absolute security and absolute insecurity are polar opposites: they do not intersect. In practice, however, the network state is usually somewhere in between in most cases. When the network is absolute secure, the network's operational state tends to be more secure; otherwise, it tends to be more precarious. Therefore, it is urgent to study the short-term prediction of virtual resource load.

3.1 Cloud Computing Virtual Resource Load Transfer Channel Model

Load balancing is a kind of computer network methodology that is applied to achieve the best utilization of computer cluster resources, network resources, CPU resources, disk resources and other resources. Load balancing technology can maximize throughput, minimize response time and prevent overload. In cloud computing, virtualization and server cluster are the two most important technologies, and load balancing technology can improve their operational efficiency. Initially, load balancing technology only distributed user requests and task requests to servers in the form of a static algorithm to improve their resource utilization. However, with the increase of requests, the tasks assigned to the nodes with weak computing power take a long time to be processed. The waiting time is long, the processing delay increases, and the efficiency of the overall system decreases. With the development of cluster technology, load balancing technology has also made great progress, making possible the dynamic allocation of tasks. According to the status of each node in the cluster, the service or application requests can be allocated or migrated as far as possible to the nodes with a low load, and through virtualization technology, the target virtual machine of the overloaded node can be migrated to the target server with low load, greatly improving the cloud data heart response speed and more reasonable use of resources, thereby avoiding unnecessary power consumption and wastage of idle resources.

The dynamic load balancing strategy aims to reduce communication delay and task execution time, so it is suitable for large distributed systems. It depends on the combination of the host attributes at runtime. When it assigns a request task to a node, it may also dynamically allocate the request task to other nodes through the collection and calculation of the node attributes. Compared with the static strategy, this strategy is more accurate and reliable, and can more effectively guarantee the load balance of a cloud data center.

The dynamic load balancing strategy has five major components:

(1) Transport policy: This policy load determines when a request task needs to be transferred from one node to another.

(2) Selection strategy: This strategy focuses on the selection of processors for load transmission so as to improve the overall response time.

(3) Allocation positioning strategy: This strategy determines the availability of the required resources, provides services, and selects resources according to their location.

(4) Information policy: This policy needs to know the workload-related information of the system, such as the workload and average load of each node. It is also responsible for information exchange between nodes. There are three ways to do this: 1) When there is a broadcast medium in the system, the load information exchange is completed when the load changes; 2) the global system load method assumes that all nodes are overloaded when one node does not recognize the recovery from another node in the complementarity phase; 3) a voting method is applied so that when a node is idle or overloaded, its neighbor node or random polling node will send a request for information.

A centralized adaptive channel allocation scheme is adopted to achieve the prediction of link robustness during the load allocation of virtual resources in cloud computing (Ke et al., 2014). The route forwarding protocol for this allocation can be expressed by the following formula for the decomposition of characteristics:

$$Z^N = g \cdot X^N + W^N \tag{1}$$

where $Z^N = (z_1, z_2, \cdots, z_N)^H, X^N = (x_1, x_2, \cdots, x_N)^H, W^N = (w_1, w_2, \cdots, w_N)^H$, and $N = 1, 2 \cdots$ are all random variables representing the source, main channel, and eavesdropping channel of the cloud computing virtual resource load allocation channel (Ma et al., 2015).

According to the bandwidth relation of the link transmission channel of the sensor network, the random probability distribution model of the equalization configuration of the adaptive channel allocation is obtained with $P_C = \sum_{i=0}^{n} \sum_{j=0}^{n} \alpha(i, j) P(i, j)$, and the channel occupancy bandwidth allocated by the cloud computing virtual resource load is obtained with:

$$U_{v_i} = \beta_{v_i} \times \log\left(1 + \partial_{v_i} \times \sum_{j=1}^{K} S_{v_i} e_j^T \frac{R_{C_j}}{n_{C_j}}\right), v_i \in v, C_j \in C \tag{2}$$

where $n_{C_j} = \sum_{j=1}^{K} S_{v_i} e_j^T$, $e_j^T = (0, \ldots, 1, \ldots, 0)$ indicates the occupancy probability that the channel output link layer v_i is in the link robustness test state channel equalization configuration according to the network transmission link structure model constructed above (Nie, 2013; Ju and Zou; 2015; Lyu et al., 2016).

3.2 Spread Spectrum Processing for Data Forwarding Channels

The processing technology applied to cloud data is different from traditional data center processing in the following aspects:

(1) Geographical location is different. The processing technology applied to cloud data is mainly used in the optical access network, which is closer to the service side, while the data center is usually located in the backbone network or the core network, which is far away from the user side.

(2) Different business processing capabilities. Compared with the data center, the data processing and storage capacity of cloud data processing technology is very limited. At present, the data cloud processing technology usually focuses on solving some simple and high-frequency business request types.

(3) The distribution is different. Data cloud processing technology is a distributed data processing method, so virtualization technology can increase the data processing ability of data cloud processing technology to a certain extent. Data center technology is a large centralized data processing method.

(4) The interaction is different. It is very difficult for a centralized data center to achieve seamless support for a variety of different operators. The distributed edge data center structure can solve the heterogeneous problems produced by different suppliers, such as the interoperability problem caused by streaming media.

In view of mobile data cloud processing technology, data cloud processing optical network architecture attempts to deploy distributed data processing units, including computing, storage, etc., close to the user side or business side. However, the introduction of data cloud processing technology in optical networks cannot perfectly overcome all the challenges faced by a flexible optical network. The adoption of data

Table 1 Cloud Computing Virtual Resource Load Allocation Node Sends Data Status Table.

Node state	Network link state (Robustness 1, Non-Robustness 0)
1. Node i is busy	$u1 = u2 = \ldots ui = \ldots = um = 0$
2. The number of hops is less than the load of the node	Network link equalization control $ui = uj = 0$
3. There is and only one node is sending data	The output compression ratio is $\rho = N/M$

cloud processing technology needs to address the following challenges:

(1) Synchronization of services. The introduction of data cloud processing technology increases the traditional secondary cloud processing structure to a three-level architecture. The data processing in this structure involves user and data cloud processing, user and cloud computing, and communication between data cloud processing and cloud computing.

(2) Seamless service. Due to the distributed characteristics of data cloud processing technology, network service requests are usually accompanied by mobility and intermittence. Therefore, a seamless service delivery needs to consider the switch mechanism in the distributed data cloud processing server.

(3) Service-oriented architecture. A service-oriented network architecture needs to be established to enable the interaction between users and servers. Because of the distribution of data cloud processing technology, the service itself may exist in multiple edge servers, or in both the edge servers and the data centers. Therefore, the establishment of a service-oriented architecture is can facilitate the handling of complex problems.

(4) Uncertainty of services. A data cloud processing server usually does not have the comprehensive data processing ability of a data center, and its data processing ability is very limited; hence, the data cloud processing service cannot guarantee its data processing ability. On the basis of constructing the link routing node channel model of wireless sensor network, the spread spectrum processing of data forwarding channel is carried out by wireless random sequence scheduling technology (Huang and Liu, 2016). In the queue of cloud computing virtual resource load allocation, the load formula of channel fractional interval balancing is given as:

$$T(n) = \sum_i R(n, i) + T(n+1) \tag{3}$$

Where $T(n+1)$ represents the transmission load of the network in layer $n+1$. The data forwarding protocol is designed using the cloud computing virtual resource load allocation status table shown in Table 1 to construct a routing detection algorithm for channel equalization configuration.

p_i is used to represent the probability that the first node successfully sends the data packet forwarding to a network link The corresponding clustering data fusion weight is w_i, the approximate center point $G_{CH} =< V_{CH}, E_{CH} >$ of clusters. A subset of one is calculated to obtain the communication range of nodes (Sun et al., 2014). A finite sink combination of cloud computing virtual resource load forwarding is constructed and represented as a set, and a graph V_{CH} is introduced, wherein the cluster data fusion weight is composed of sink nodes and nodes, and the channel spread spectrum output is obtained as follows:

$$x(t) = \mathrm{Re}\left\{a_n(t)e^{-j2\pi f_c \tau_n(t)} s_l\left(t - \tau_n(t)\right) e^{-j2\pi f_c t}\right\} \tag{4}$$

where the bandwidth of cloud computing virtual resource load distribution can be described as:

$$c(\tau, t) = \sum_n a_n(t)e^{-j2\pi f_c \tau_n(t)} \delta\left(t - \tau_n(t)\right) \tag{5}$$

where, $a_n(t)$ is the spread spectrum bandwidth on the nth transmission link, $\tau_n(t)$ is the transmission delay of the nth transmission link, f_c is the modulation frequency of the transmission link, and $s_l(t)$ is the oscillation amplitude of the output transmission link (Metwally and Faloutsos, 2012).

4. SHORT-TERM LOAD FORECASTING ALGORITHM FOR CLOUD COMPUTING VIRTUAL RESOURCES

4.1 Multi-Granularity Weighted Control Algorithm

In order to construct the link forwarding routing node channel model of the wireless sensor network, and adopt the wireless random sequence scheduling technology to carry out the spread spectrum processing of the data forwarding channel, the optimization design of the cloud computing virtual resource load short-term prediction algorithm is carried out (Hashemi and Yang, 2009). This paper proposes a link robustness prediction algorithm for cloud computing virtual resource load distribution based on OpenStack. The non-cooperative game model of cloud computing virtual resource load distribution is constructed as follows:

$$\begin{cases} \max U = u_1 + u_2 + \ldots + u_n \\ u_i = p_i \\ \sum\limits_i^n p_i = 1, 0 < p_i < 1 \\ \frac{p_l/(1-p_l)}{w_1} = \frac{p_i/(1-p_i)}{w_i} = .. = \frac{p_n/(1-p_n)}{w_n} = \frac{1}{K} \end{cases} \tag{6}$$

Considering the random game nature of k value, the adaptive weight of cloud computing virtual resource load distribution is w for n competing channels, $K = (n-1)w$.

The modulation component $h_i'(t)$ for calculating link robustness prediction is adopted to obtain the channel idle bandwidth $h_i(t)$ allocated by cloud computing virtual resource load, which is described as a convolution $h_i'(t) * h_i'(-t)$ of the two, and is:

$$h_i'(t)^* h_i(-t) \cong h_i'(t)^* h_i'(-t) \cong \delta(t) \tag{7}$$

Using the link-forwarding routing node adaptive modulation method, the reduced amplitude of the channel is $p_i = r_i p_0$. Calculate the channel impulse response of the output terminal to obtain the relation $K_0 = (m-1)w_0$ and $p_0 = \frac{1}{m}$, between the channel transmission delay and the multi-granularity adaptive weight value $m = r_1 + r_2 + \ldots + r_i + \ldots + r_n\, e$, and carry out robustness prediction by applying the multi-granularity adaptive optimization method to obtain a multi-granularity weighted model which is described by a function as follows:

$$\begin{aligned} E_{init} &= E_R + E_T + E_F \\ &= \sum_{r=1}^{L_i} \sum_{n_j \in S_i^r} E_{Rx}(l) + \sum_{r=1}^{L_i} \sum_{n_g \in N_i^r} E_{Tx}\left(l, d_{(n_i,n_g)}\right) \\ &\quad + \sum_{r=1}^{L_i} l_r E_{DF} \\ &= \sum_{\mathrm{r}=1}^{\mathrm{L_i}} \left\{ \sum_{n_j \in S_i^r} E_{Rx}(l) + \sum_{n_g \in N_i^r} E_{Tx}\left(l, d_{(n_i,n_g)}\right) \right. \\ &\quad \left. + l_r E_{DF} \right\} \end{aligned} \tag{8}$$

Under the constraint of multi-granularity weighting, the energy consumed in sending data by the number of candidate cluster heads is:

$$E_T = \sum_{r=1}^{L_i} \sum_{n_g \in N_i^r} E_{Tx}\left(l, d_{(n_i,n_g)}\right) \tag{9}$$

The cluster head nodes n_j and sink of the wireless sensor network perform single-hop control, and the energy consumed for data fusion in L_i is:

$$E_F = \sum_{r=1}^{L_i} l_r E_{DF} \tag{10}$$

According to the above analysis, a multi-granularity weighted control method is combined to carry out channel equalization design in cloud computing virtual resource load distribution, and multi-granularity adaptive optimization is adopted under discrete multi-path conditions (Ju and Zou, 2015).

4.2 Prediction of Link Robustness in Network Link Allocation

Under the constraint of granularity weighted control, a link spread spectrum method is adopted to improve the channel throughput, and a bandwidth calculation formula for computing the cloud virtual resource load distribution is obtained:

$$I(i) = \sum_{j \in inf(i), j \neq i} T(j) \tag{11}$$

where $Intf(i) = B - \frac{L\mu(i)}{128512}$, B is the channel throughput of cloud computing virtual resource load distribution (Lyu et al., 2016; Yang, 2018).

Initial feasible solution process:

(1) Process each virtual link in the virtual request GV;

(2) For the start node , the physical node with the maximum value and unassigned is used as the mapping node;

(3) The mapping node of the end node eNode should:

   (a) not be currently assigned;
   (b) be within the range of the number of hops of the starting node, nhop;
   (c) have the maximum value within the hop range and satisfy the virtual node resource request;
   (d) be among all the shortest paths between the start mapping node and the start mapping node, (select a path with a bandwidth not less than the virtual link bandwidth and the minimum load balance degree of the current link); and
   (e) be the remaining resources of the intermediate nodes through which the entity mapping link passes.

(4) If the starting node is not mapped and the ending node is mapped, the physical node mapping the starting node must meet the conditions in (3);

(5) If the start node and the end node are mapped, then one of the shortest paths between them is selected to ensure that the bandwidth is not less than the virtual link bandwidth, and the current link has the minimum amount of load balancing.

(6) Repeat the above process to generate a fixed number of different initial mapping particles, so that the virtual network mapping can eliminate the bottleneck of network resources under the condition of controllable resource consumption, get a more balanced underlying physical network, and improve the success rate, utilization rate of network resources, and income of infrastructure providers of the subsequent virtual network mapping. For each virtual node in the particle, according to the adjustment probability, the entity node is randomly selected to replace the original mapping node. The new entity node meets the following constraints:

   (a) not previously allocated;
   (b) within the range of hop number nhop;
   (c) node resources meet the requirements of virtual node CPU resources;

(d) Among all the shortest paths between the initial mapping node and the final mapping node, the path whose bandwidth is not less than the virtual link bandwidth and the minimum load balance of the current link is needed;

(e) The entity mapping link needs to pass through the intermediate node of the link;

(7) If the link resource of the particle satisfies the bandwidth constraint at this time, step (8) will be executed, otherwise go to (6) to reselect the particle;

(8) Update GB, Pb and GB, where GB is calculated by adjusting a and B according to Equation (12);

(9) After all particles are processed, skip (1) to the next iteration; otherwise, skip (3) to the next particle;

(10) After all iterations are completed, the success rate of virtual request reception, the overall load balance of the network, and the revenue of the infrastructure provider in this time unit are calculated. According to the clustering density of each round, the route distribution scheme for obtaining short-term prediction of wireless sensor cloud computing virtual resource load is expressed as follows:

$$p_i = \frac{r_i}{m} = \frac{r_i w_0}{m w_i} = \frac{w_i}{w_1 + \ldots + w_i + \ldots + w_n} \tag{12}$$

In the cluster head selection phase, the channel correlation feature matching process and equalization configuration are carried out. Under the multi-hop routing strategy, the competition model of link prediction is as follows:

$$\alpha(i, j) = \begin{cases} 0, i = 0 or j = 0 \\ 1, n - j < i, i \geq j \\ 1, n - i < j, j \geq i \\ 1 - {}_{n-j}C_i / {}_nC_i, n - j \geq i, i \geq j \\ 1 - {}_{n-i}C_j / {}_nC_j, n - i \geq j, j \geq i \end{cases} \tag{13}$$

$\sum_{j=1}^{K} S_{v_i} e_j^T \frac{R_{C_j}}{n_{C_j}}$ is used to represent the life cycle of node ni, and the message transmission energy cost in the clustering phase is expressed as:

$$U = \sum_{v_i \in V} U_{v_i} = \sum_{v_i \in V} \beta_{v_i} \times \log \left(1 + \partial_{v_i} \times \sum_{j=1}^{K} S_{v_i} e_j^T \frac{R_{C_j}}{n_{C_j}} \right) \tag{14}$$

Select the node with the largest $E_{res}/Computition(n_j)$ as the route forwarding node for cloud computing virtual resource load distribution. The set of nodes sending data is:

$$a(t) = \sum_{n=0}^{\infty} a_n g_a(t - nT_a) \tag{15}$$

The impulse response function of the corresponding cloud computing virtual resource load list in the idle state is:

$$p(t) * p(-t) \cong \delta(t) \tag{16}$$

At this time, the conflict ratio of cloud computing virtual resource load is CCP:

$$CCP(i) = \frac{NCN(i)}{\sum\limits_{j=1}^{CN} NCN(i)} \tag{17}$$

At the receiving end of cloud computing virtual resource load, based on OpenStack, the predicted value of transmitted data of K nodes is as follows:

$$W = \alpha \frac{E_{res}}{E_{init}} + \beta \left(1 - \frac{d\left(n_i, n_j\right)}{d_0} \right) + \gamma \left(1 - \frac{d_j - d_{\min}}{d_{\max} - d_{\min}} \right) \tag{18}$$

where $\alpha + \beta + \gamma = 1$, $\alpha(i, j)$ represents the sending state of the node in the state, and adopts a multi-granularity weighting model to achive link robustness prediction in cloud computing virtual resource load distribution. The implementation process is shown in Figure 3.

5. SIMULATION TEST ANALYSIS

In order to test the performance of the design method applied to link robustness prediction in cloud computing virtual resource load distribution, a simulation experiment is carried out. The underlying network topology is set to have 100 nodes. The link probability of the node is 0.02. CPU resources and bandwidth resources of the underlying network nodes are evenly distributed between 50–100. It is assumed that the arrival of virtual network requests obeys the Poisson process with the time unit of 100 and the intensity of 5, and the lifetime of each virtual network obeys the exponential distribution with the parameter of 400. For each virtual network request, the number of virtual network nodes follows a uniform distribution of 2 to 10, and each pair of virtual network nodes are connected with a probability of 0.5. The CPU resource and link bandwidth resource requirements of virtual network nodes are uniformly distributed from 0 to 50. The experimental algorithm design is built on the Matlab platform, and the wireless sensor network design is built on the OMNet++ platform. Cloud computing virtual resource load distribution is divided into four data transmission channels, and the symbol width of link transmission is 0.25 ms. The MAC layer transmission control protocol IEEE 802.1 of the wireless sensor network has a simulation time length of 100s for link prediction, a simulation time round of 1000, and the number of cluster heads set to be 0–15 random. Simulation analysis is carried out in this simulation environment and parameter setting. The results for the number of rounds of nodes using different methods for network link prediction under different cluster head number distributions are reported and compared in Figure 4.

Analysis of Figure 4 shows that the proposed method can effectively increase the number of output rounds of network link nodes, thus improving the activity and balance of link forwarding, and testing the energy consumption of the network and the residual energy of nodes. The comparison results are shown in Figure 5 and Figure 6.

Analysis of the results shown in Figure 4 and Figure 5 shows that by using this method to predict the load of cloud

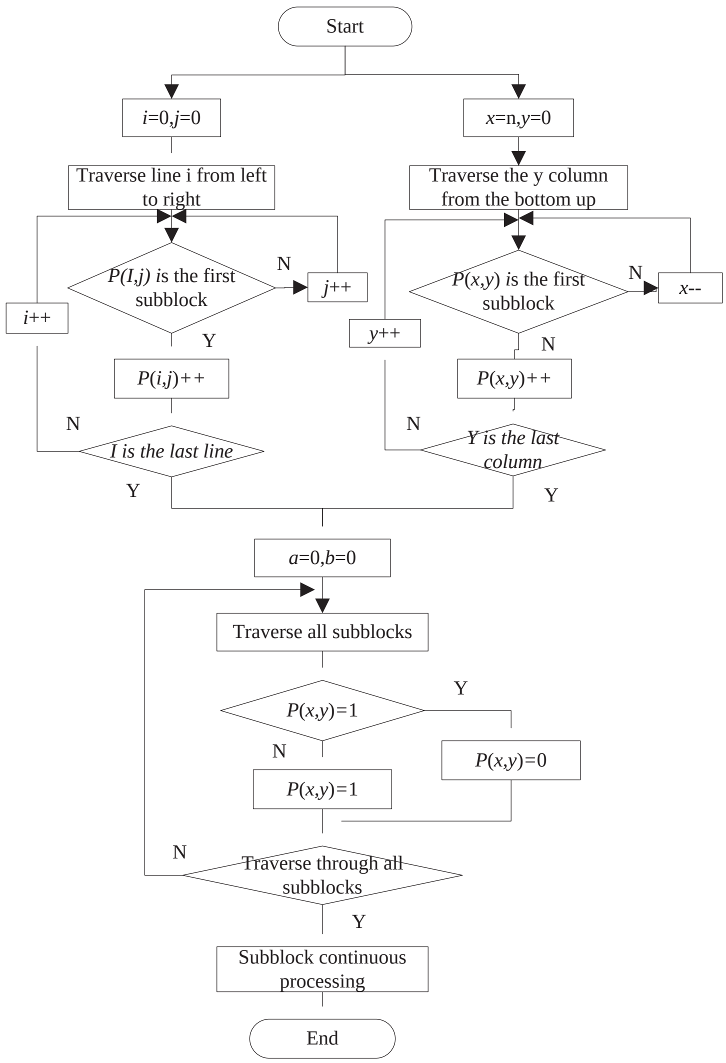

Figure 3 Flow Chart of Algorithm Implementation.

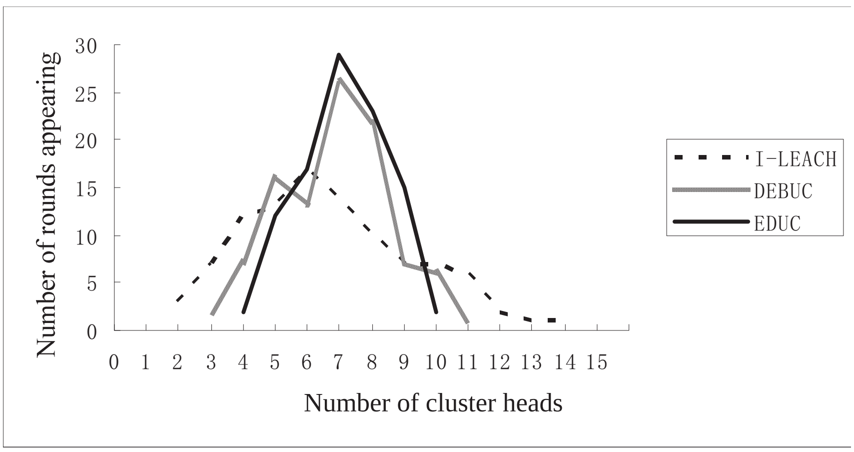

Figure 4 Comparison of Output Rounds of Network Link Nodes.

computing virtual resources, the energy consumption is lower, the remaining energy of nodes is the largest, and the viability of the network is improved.

Further, we need to consider the resource consumption of intermediate nodes on the underlying physical path of virtual link mapping. Hence, in the next step, we conduct an experiment and measure this index, and study its impact on virtual network mapping. The test results are shown in Figure 7.

The simulation results show that after reducing the consumption of forwarding packets, the underlying physical resources can eliminate the bottleneck of network resources,

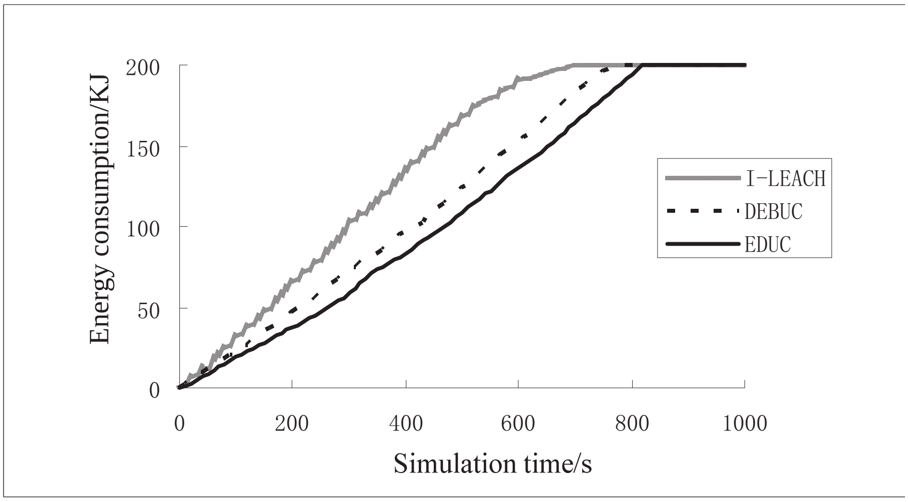

Figure 5 Comparison of Network Energy Consumption.

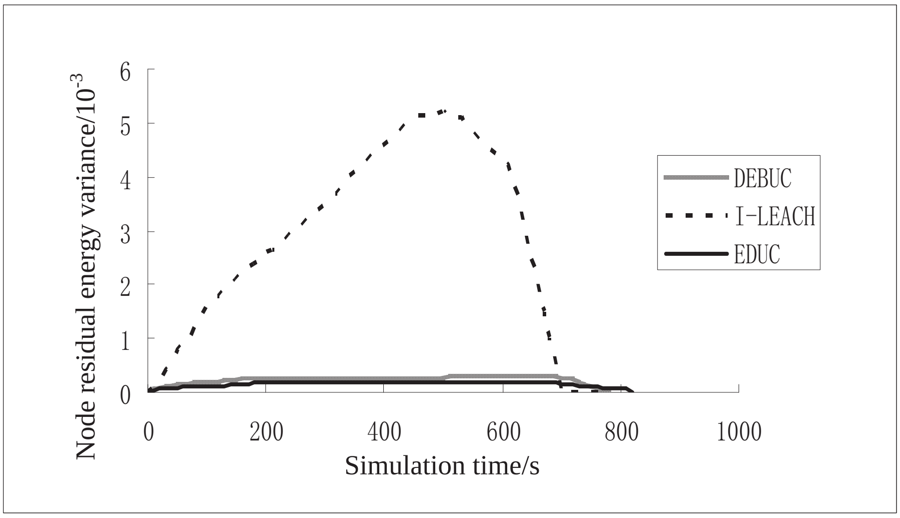

Figure 6 Comparison of Residual Energy of Nodes in Network.

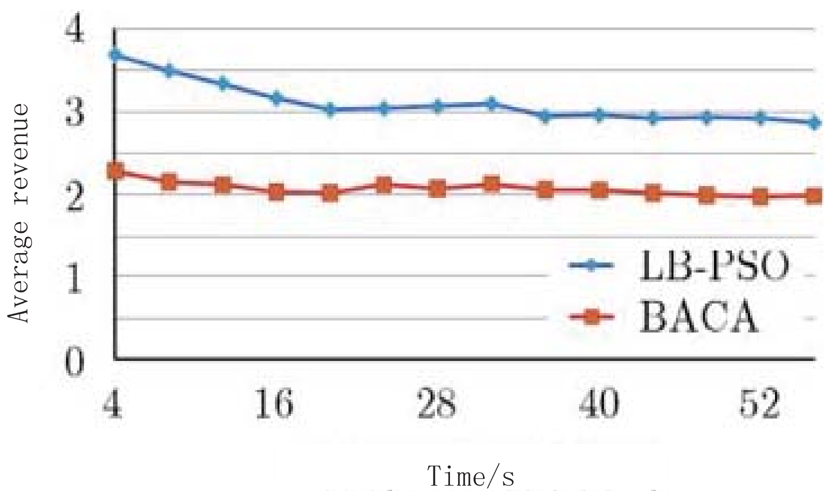

Figure 7 Average Revenue Test Results.

provide a more balanced underlying physical network for subsequent virtual network requests, improve the success rate of virtual network construction, the utilization rate of network resources and the income of infrastructure providers, and limit the mapping of virtual links to underlying physical paths. During virtual network mapping, the number of hops ensures the resource balance of the underlying physical network and uses the physical resources as little as possible, so as to

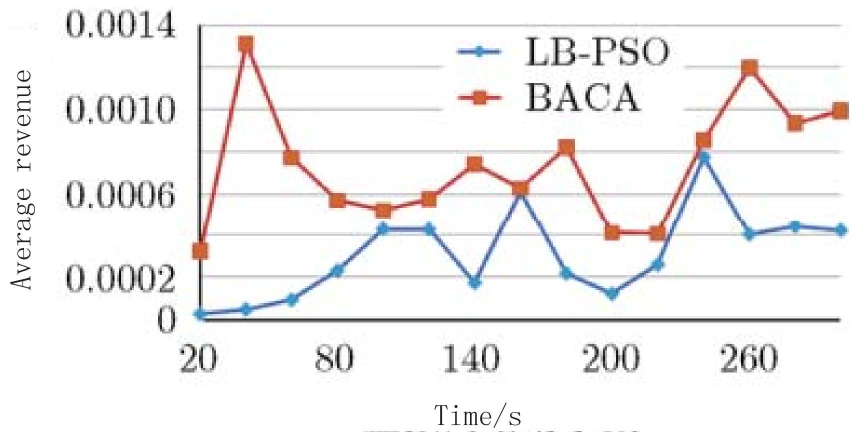

Figure 8 Comparison Test Results.

reflect as many virtual networks as possible in the physical network with limited resources and maximize the interests of infrastructure providers. Finally, through experimental comparison, five advantages of the algorithm are verified: the success rate of virtual request reception, the balance degree of the whole network after mapping, the load balance degree of nodes, the load balance degree of links and the average income of infrastructure operators.

It can be seen from Figure 8 that for the arriving virtual network request, the load balance degree of the link using the proposed algorithm is lower and more balanced than that achieved by Baca. In the process of virtual network mapping, on the one hand, the algorithm adaptively adjusts the node weight and link weight in the objective function according to the status of the underlying physical resources (including node resources and link resources) and, on the other hand, it takes the link load balance as the optimization objective.

6. CONCLUSION

In order to improve the load distribution efficiency and channel balance of virtual resources in cloud computing, a link robustness prediction algorithm for load distribution is proposed based on OpenStack. A link-forwarding routing node channel model of wireless sensor networks is constructed; a wireless random-sequence scheduling technology is adopted to carry out spread spectrum processing of data-forwarding channels; a multi-granularity weighting control method is combined with to carry out channel equalization design in cloud computing virtual resource load distribution, and a multi-granularity adaptive optimization method is adopted to achieve link robustness prediction in cloud computing virtual resource load distribution. The research shows that the link robustness prediction in cloud computing virtual resource load distribution using this method has greater accuracy, stronger anti-interference, lower energy consumption, higher node activity, and improved network viability and link-forwarding activity. There are still many problems in virtual network mapping that need to be studied and solved. At present, the relevant research work is mainly focused on mapping the virtual network requests with quantitative network resource requirements effectively Due to the scarcity of network resources, in subsequent work, we consider modeling and solving the virtual network request of dynamic resource requirements.

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