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Forecasting Research on the Wireless Mesh Network Throughput Based on the Support Vector Machine

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Abstract Parameters such as network busy rate, number of nodes as well as packet size that affected the wireless mesh network (WMN) throughput were selected as the driving factors which restricted the WMN throughput. A WMN throughput prediction model has been developed based on machine learning methods and experimental study to predict the throughput of IEEE 802.11 WMN. Three kernel functions have been testified and compared through MATLAB. The radial basis kernel function was selected as the support vector regression (SVR) kernel function predication model and its parameters were decided by K-fold cross validation (K-CV) and grid search methods. The proposed prediction model was validated by the data which was simulated in network simulator (NS2). In addition, a prediction model of Mesh network throughput has been established based on back propagation neural network (BPNN). The performance of the models were evaluated using the mean square error and mean absolute error. The experimental results show that the prediction precision of the proposed SVR-based model is a little bit higher than that of the BPNN model. The establishment of the WMN throughput prediction models provides the basis for building, managing and planning rational network structures.

Keywords Wireless mesh network · Support vector regression · Back propagation neural network (BPNN) · Network throughput prediction

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1 Introduction

WMN is a new kind of multi-hop access network with self-organizing and self-managing wireless architecture. It is featured with self-organizing, low cost, rapid expansion and many others, which is considered as a solution to the "Last Mile" problem of wireless network access [1, 2]. With the wide application of WMN and the emergence of multimedia services, such as network multimedia, the bottleneck of WMN has been exposed. It not only causes the decline of network quality of service (Qos), but also imposes a threat to the entire WMN security. It could even make the network paralyzed if the network load goes beyond the network capacity to a certain limit. Therefore, the research on the WMN throughput earns great concern. Through the evaluation of WMN throughput, major factors affecting Qos can be comprehensively analyzed and problems in network topology, routing design and network deployment could be identified [3].

In recent years, as a new type of learning machine, support vector machine (SVM) has received more and more attention. It has extended from the pattern recognition to classification and regression estimation. Great progress has also been made in modelling and predicting the nonlinear system through SVR [4–6]. Based on the statistical learning theory and structural risk minimization principle, SVR overcomes the limitations of the traditional statistical theories when the sample size approaches infinity, and it tackles problems in empirical nonlinear methods, for example, problems of the network structure, overfitting, and local minimum in nonlinear optimization. Therefore, it is a novel and promising research direction in nonlinear modeling with the method of SVR.

SVM and SVR are widely applied to all fields of network research. Bermolen and Rossi [7] used SVR to predict link load. Beverly et al. [6] designed a SVM model for predicting round trip delay. In addition, Feng et al. [8] proposed a wireless network traffic prediction method using SVM. Mirza et al. [9] proposed a throughput prediction method based on SVR, which combined the existing data transmission and network measurement metrics such as packet loss, queuing delay and available bandwidth. In the Ref. [10], Lee specialized in measuring and analyzing the throughput of Internet and established the model to predict the results accurately. In paper [11], factors affecting the prediction results were discussed, and the v-SVR and polynomial kernels were used to establish a continuous monotonic function prediction model. The accuracy of the proposed method has been compared with that of the method in paper [10], and the experimental results showed that the accuracy of the proposed method was higher to that of the method in paper [12]. A large number of SVR were used in the prediction of network traffic. Feng et al. [8] established a wireless network traffic prediction model based on SVM model and the experiment showed that the SVM-based prediction model could provide more accurate prediction.

At present there are few reports on the throughput prediction of WMN which is focused on the performance prediction relying on the traffic pattern or routing protocols [13, 14]. Reference [13] evaluated the performance of routing protocols in WMN from the aspect of network traffic complexity. A linear traffic predictor was developed for reliable and resilient video communications over multi-location WMNs [14]. In order to explore a generalized prediction method for WMN based on the machine learning methods, this paper studies the driving factors affecting WMN performance, simulates different topologies of WMN, and proposes a WMN throughput prediction method based on machine learning methods. It provides a new research method and solution for guiding and optimizing the wireless network system.

2 Network Model and Problem Description

2.1 Network Model

Akyildiz and Wang [2] classified WMN architectures into two types: the client WMN and the infrastructure backbone WMN based on the node function. The backbone WMN architecture includes 2 types of nodes, namely the wireless Mesh gateway and the wireless Mesh router. In the infrastructure backbone WMN, wireless routers are connected to the Ethernet through wireless Mesh gateway. Wireless routers can also be integrated with all kinds of wireless networks such as Wi-Fi, sensor network, cellular network and WiMAX network. In addition to basic functions such as routing and relay, Mesh router network also has the unique function of network interconnection. It can communicate in a larger area through multi hops and obtain same signal coverage with low signal transmit power. This paper is mainly based on the throughput of wireless Mesh router in backbone WMN.

2.2 Problem Description

Throughput is one of the most critical parameters that ensure the services of WMN to meet the requirements of customers. Throughput capacity of multi-hop wireless networks has been studied in other papers. Gupta and Kumar [15] derived the per-node throughput capacity for static ad hoc networks. The throughput capacity of mobile ad hoc networks was analyzed by Grossglauser and Tse [16]. The capacity of hybrid ad hoc networks was investigated in [17–19]. All such results of throughput analysis cannot be applied to WMN, because the network architecture of WMN is quite different from either conventional ad hoc networks or hybrid ad hoc networks. In this paper a throughput prediction model is derived to predict the throughput of WMN. By the machine learning methods, the relationship between driving factors affecting WMN performance and throughput is studied. There are a lot of metrics to measure WMN throughput, such as network path, end-to-end delay, the number of nodes, the number of available orthogonal channels, the load flow, etc. To predict the WMN throughput, it is very important to study these metrics because they can offer first-hand information for predicting the throughput of the network. The throughput distribution has some common features on WMN, otherwise the prediction will doom to fail if it is completely random. There are 2 kinds of WMN performance abstract models. One is the general wireless network, and the other is the wireless network based on IEEE 802.11. The WMN research in this paper is based on IEEE 802.11 and the WMN throughput prediction has been studied from the following 4 aspects:

1. Data sources

For the success of a prediction model, data sources reliability plays a key role. A good prediction model could also fail if the data sources are unreliable and error prone. Therefore, the process of collecting data must be objective, comprehensive, specific and accurate. Data in this paper were obtained from the simulation results of NS2. They were collected every 100 s, and each network simulation scenario was run 13 times in order to average the results, which ensured the objectivity and accuracy.

2. Influence factor

The level of WMN throughput depends not only on the hardware environment, but also on the parameters of the simulation environment, network topology, bandwidth and routing paths. In this paper, the key factors affecting the throughput of WMN were set as the independent variables in the prediction model.

3. Prediction model

There are history-based approach and formula-based approaches on the modeling and prediction of WMN throughput. The history-based approach is based on the analysis of the past throughput in a time series. The formula-based approach takes the throughput as a mathematical function based on network characteristic parameters. BPNN and SVR are two typical formula-based models. BPNN is widely used and obtains good results for solving the nonlinear regression problem. The SVR provides a new way to address the problem of low prediction accuracy due to the small sample size in BPNN prediction. SVR is the regression form of SVM. It specializes in machine learning with limited samples, minimizes structural risks, solves the convex quadratic programming problem, and realizes global rather than local optimality in BPNN. When using SVR to solve practical problems, the nonlinear variation will be transformed into the high dimensional space and achieves nonlinear decision function through the linear decision function constructed in the high dimensional space. It has good generalization ability where the complexity of the algorithm is independent of the dimensions of the samples. SVR currently is widely used in the fields of regression estimation and pattern recognition. Therefore, the network throughput prediction model based on SVR may have higher prediction accuracy compared with that based on the BPNN.

The key to the prediction model based on BPNN is the selection of network structure and the optimization of input parameters. It needs a large number of samples in order to achieve satisfactory results. The selection of SVR kernel functions and its parameters are critical to set up a prediction model based on SVR.

In this paper, the grid search-10 cross validation method was used to optimize the parameters in the Radial Basis Function (RBF). The throughput prediction model of WMN based on SVR was established. The effectiveness of the prediction model based on SVR was testified by comparing with the results of WMN throughput prediction model based on BPNN.

3 Construction of WMN Throughput Prediction Model

To improve the performance of the whole WMN, the network delay and the maximum throughput become the research focus [20]. Network throughput is defined as the maximum available bit rate available to WMN. The network delay can be defined as the average interval between the starting and ending of a data packet in the WMN backbone network considering queuing delay and transport delay. Network delay and network throughput are 2 closely related indicators in WMN. Therefore, network throughput has been taken as a sign of improving network performance.

3.1 Selection of Driving Factors

The changes of the throughput of WMN network is the result of the interaction of many kinds of factors [21]. In this paper, 7 driving factors were selected, including the network busy rate, total amount of transmitted data, type of transport layer protocol, node number of sending data, total node number, network topology and packet size, as independent variables in the SVR prediction model.

3.2 Introduction of SVR

SVM is proposed for the classification problem, while SVR is a model of support vector in fitting regression problems. Through establishing the nonlinear relationship between the vector to be predicted and the support vector, vectors have been predicted. The formulas and derivations in this paper are derived from the literature [22, 23]. For SVR, the input data is assumed to be $\{(X_1, y_1), \ldots, (X_n, y_n)\}$, in which $X_i \in X^d$ is the input vector of d dimension, and y_i is the measured value when $X = X_i$. The derived function is like follows:

$$f(x) = W^T \mathrm{X} + b \tag{1}$$

Similar to the case of classification, it is necessary to determine the value of the weight vector and the intercept b in y-axis. The goal is to find a smooth W, i.e., a small W. W can be defined as the minimization criterion $|W||^2 = W^{\mathrm{T}} W$ which is applied to SVR. SVR adopted ε-insensitive loss, as its minimization constraint. The goal of ε-insensitive loss is to find a function $f(x)$ that can deviate from the measured value. The error greater than ε was unacceptable or punished. The optimization of SVR can be written as:

$$\min \frac{1}{2} \|W\|^2 \tag{2}$$

subjected to:

$$W^T X_i + b - y_i \geq -\varepsilon \text{ or } W^T X_i + b - y_i \leq \varepsilon \tag{3}$$

In order to minimize the Euler norm $||W||^2$, slack variables ξ_i, ξ_i^* and penalty factor C have been introduced. The optimization of SVR with slack variables have changed into

$$\min \frac{1}{2} \|W\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \tag{4}$$

subjected to:

$$W^T X_i + b - y_i \geq -\varepsilon - \xi_i^* \text{ or } W^T X_i + b - y_i \leq \varepsilon + \xi_i (\xi_i, \xi_i * \geq 0) \tag{5}$$

Similar to SVM, the optimization of SVR can be easily solved by its dual form and Karush–Kuhn–Tucker (KTT). The complete derivation formula can be found in [6], and the final regression model has been obtained as

$$f(x) = W^T \mathrm{X} + b = \sum_{i}^{1} (\alpha_i^* - \alpha_i) K(x_i, x) + b \tag{6}$$

Among them, α_i^* and α_i are Lagrange multipliers. $K(x_i, x) = X \cdot X_i$ is the kernel function, of which X_i is the feature space of the training sample, and X is feature space of the testing sample. Different kernel functions could be selected to solve different problems.

3.3 Selection of Kernel Function Parameter

For the SVR model, the results and accuracy are quite different with the different kernel functions. Moreover, the introduction of the kernel function greatly improves the nonlinear processing ability of learning machine. It also keeps the inherent linearity of the learning machine in the high dimensional space, thus it's easy to control the learning machine. At present, there are four kinds of kernel functions in support vector regression:

1. Linear Kernel Function(LINEAR)

$$K(x, x_i) = x^T \cdot x_i \tag{7}$$

2. Polynomial Kernel Kernel Function (POLY)

$$K(x, x_i) = [(x \cdot x_i) + coef]^d \tag{8}$$

   Among them, d is thepolynomial degree, $coef$ is the paranoid coefficient.
3. Radial Basis Kernel Function(RBF)

$$K(x, x_i) = \exp(-\gamma||x_i - x||^2) \tag{9}$$

   Among them, γ is the Kernel radius of RBF.
4. Sigmoid Kernel Function(SIGMOID)

$$K(x, x_i) = \tanh[\gamma(x_i \cdot x) + coef] \tag{10}$$

K-CV method is used to determine the optimum parameters for these kernels [24]. The parameters of the penalty parameter c and the kernel function parameter g are determined by adjusting the parameters repeatedly to reach satisfactory accuracy. The parameters of kernel functions are roughly optimized where the range of c, g is [0-210] and in the fine optimization process the range of c, g and the final results are shown in Table 1. It is found that the MSE of the RBF is the lowest where MSE = 0.0286, so the RBF is used in the SVR prediction model in this paper.

3.4 Evaluation of Predictive Accuracy

Equations (11) and (12) are used to check the performance of the prediction models [25]. Mean squared error (MSE) is given by;

Table 1 Fine optimizations of kernel function parameter

Kernel function	Parameter	Fine optimizations of kernel function parameter		
		Best parameter	Fine range	MSE
POLY	c	4	[1,9]	0.0687
	g	2.8284	[− 4,4]	
RBF	c	11.3137	[− 4,4]	0.0286
	g	0.70711	[− 2,4]	
SIGMOID	c	64	[2,10]	0.46
	g	0.0029604	[− 4,4]	

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \tag{11}$$

Mean absolute error (MAE) is given by;

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{e_i}{y_i}\right| \tag{12}$$

where n is the sample number, $e_i = y_i - \hat{y}_i$ is the prediction error, in which y_i is the actual value and $\hat{y}_i$ is the prediction value. Equation (11) evaluates the data variations. The smaller the MSE value is, the better accuracy of the prediction model can be to describe the experimental data. MAE can reflect the prediction accuracy objectively when n is small.

3.5 Construction of the WMN Throughput Prediction Model Based on SVR

The throughput prediction model is constructed by LIB-SVM software package. The package, designed by Lin Zhiren in National Taiwan University, is simple, easy, and effective to do SVM pattern recognition and regression. There are mainly two programs running in modeling, svmtrain (training modeling) and svmpredict (to use the existing prediction model) [26]. SVM type value was set as 3 to represent ε-SVR for regression. The steps are as follows:

1. The data set was prepared according to the format required by the LIB-SVM package. 50% of the data sets were randomly selected as the training data, and 10% of the data in the remaining 50% were randomly selected as the prediction data.
2. The data was normalized. In order to speed up the convergence of the training network, normalization method was adopted by using 0 and 1. The formula is,

$$y = \frac{(y_{\max} - y_{\min}) \cdot (x - x_{\min})}{(x_{\max} - x_{\min})} + y_{\min} \tag{13}$$

   where $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the original x, respectively. $y_{\min}$ and $y_{\max}$ are the mapping range of the parameters.
3. The appropriate kernel function was selected by using different kernel functions with grid search − 10 cross validation to get the best parameter c and g.
4. The lowest value of MSE was 0.0286. Its corresponding kernel function was RBF. Its corresponding optimal parameters, the value of c was 11.3137 and the value of g was 0.70711. Therefore, RBF was selected as the vector regression model to carry out experiment and prediction.

4 Experimental Design

4.1 Experimental Environment

Experimental data are from the results of NS2 simulation. NS2 is one of the most convenient and open-source network simulator [27]. NS2 network platform has many advantages and characteristics, yet also shortcomings. When simulating a bigger network or for a longer period of time, it needs enough CUP and great memory support. NS 2.35 simulation software was installed on a high performance service platform with the distributed parallel operation mode. With the advantages of multiple node cluster, parallel simulation is used to realize the fast simulation of NS2. Environment parameter settings of the cluster were shown in Table 2.

Optimized Link State Routing Protocol (OLSR) [28] was used in the simulation, with the routing metric of hops and OLSR running by UM-OLSR [29]. NS 2.35 MAC layer was set by the IEEE 802.11b protocol and the physical layer was set as IEEE 802.11b OFDM. For Carrier sense multiple access/carrier avoidance (CSMA/CA) MAC protocol, the request-to-send/clear-to-send (RTS/CTS) transmission mechanism is enabled. The settings of simulation parameter were shown in Table 3.

4.2 Network Topology

As our work is solely focused on the WMN that is characterized by a fixed backbone, node mobility is not a concern. The network node was set as a static node in the simulation. In NS2, 3 different WMN topologies were designed, which were linear, square and irregular. As shown in Fig. 1a–c, three different network topologies with 6 nodes, 12 nodes and 16 nodes were designed in the experimental part. The marked circles represented the Mesh nodes.

4.3 Data Acquisition

The test data were generated from the NS-2 simulation and the average measured results at the MAC layer throughput were obtained. They were collected for every 100 s and 2106 records were used to build the model. 10 modeling samples were listed in Table 4, in which the record number T and 7 driving factors that affected network throughput were included, namely the network busy rate X_1(%) which was calculated by Link Loads/Link Capacity [30], the total transmit data X_2 (Mb), transport layer protocol X_3 (tcp/udp), the number of nodes sending data X_4(2 nodes or 3 nodes), the total number of nodes X_5, network node topology X_6, packet size X_7 (Byte) and throughput X_8 (Mb/s). Among them, X_1 had 13 cases from 1 to 13%; X_2 had 3 cases of 6, 8, and 10 Mb; X_3 was divided into two cases of TCP or UDP; X_4 was the total number of the nodes sending the data which had two cases; X_5 represented the total number of nodes in the network which include three cases of 6, 12 and 16 nodes; X6 represented 3 types of network topologies (1, 2 and 3 represented Line, Matrix and Random topology respectively); X_7 is the packet size,

Table 2 Environment parameters of the cluster

Name	Type
Blade server	HS22
Node	Two-way Intel Xeon E5520 2.26 GHz Quad Core processors each node with 24 GB DDR3 ECC 1333 GHz memory
Node 01-node 26	1 146 GB SAS internal hard drive
Node 27-node 32	2 146 GB SAS internal hard drives
Network card	2 build-in 1000 Mbps network cards
Memory	1 2-port QDR 40 Gb InfiniBand Expansion Card (CFFh)

Table 3 Parameter setting

Transmitting power	0.2818 W
Communication distance	250 m
Carrier sensing range	550 m
Receive threshold	3.652×10^{-10} µs
Carrier sense threshold	1.559×10^{-10} µs
Slot time	0.00002 µs
Interframe space	0.00001 µs
Preamble size	144 bit
PLCP header length	48 bit
PLCP data rate	1 Mbps
Data rate	11 Mbps
Basic rate	1 Mbps

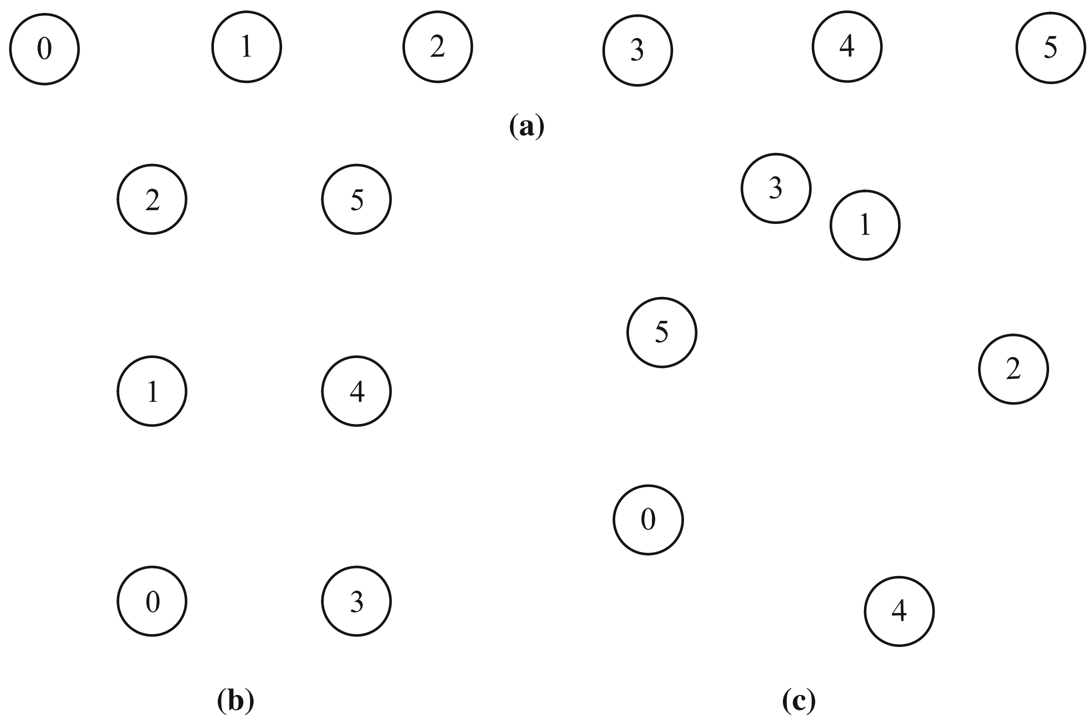

Fig. 1 Network topology of WMN. **a** Linear topology. **b** Matrix topology. **c** Irregular topology

respectively 800, 1000 and 1200 Byte. Each test case was changed in the simulations by variables control and therefore the total number of tests was 4212 times.

4.4 Experimental Results and Analysis

In order to verify the performance of the SVR prediction model, the SVR prediction model was compared with the BPNN prediction model. For a fair comparison, the parameters and thresholds of BPNN were optimized by a Genetic Algorithm (GA) [31]. The prediction error of BPNN before and after the optimization was shown in Table 5. Since the parameters in BPNN model were optimized by GA, MSE and MAE was decreased to some extent.

Table 4 Modeling samples

T	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
1	1	6	1	2	6	1	800	0.48
2	5	8	1	2	12	1	800	0.66
3	7	6	2	2	12	1	800	0.66
4	12	6	2	2	12	1	800	0.46
5	13	8	2	3	6	3	1000	0.38
6	1	10	1	2	6	1	1000	0.06
7	5	6	2	2	12	1	1000	0.47
8	12	10	1	2	6	3	1000	0.05
9	9	8	1	3	16	2	1000	1.39
10	2	10	2	2	16	2	1000	1.28

Table 5 Optimization of BPNN

Parameter optimization	MSE	MAE
Default	0.043	0.129
GA	0.027	0.113

4.4.1 Comparison of Fitting Results

The normalized training data were put into SVR and BPNN model for training and parameter optimization. The corresponding prediction model was established by using the optimal parameters. The fitting results and error of fitting were shown in Table 6. It can be seen that the fitting accuracy of SVR prediction model was higher than that of BPNN. The results from the Table 6 can be seen that SVR method had the best fitting effect, so the SVR model is reasonable and reliable.

4.4.2 Comparisons of Prediction Performance

The fundamental principle to judge the performance of the prediction model lies in its ability to predict. The prediction set has been launched into the two optimal prediction models. The MSE and MAE of the two prediction models were obtained after the 10,000 prediction tests. The result was shown in Table 7. The Table 7 showed that the prediction accuracy of the two prediction models were both very high. The predicting results were almost close to the real values that was due to the very rich modeling samples and parameter optimization. The SVR prediction accuracy was a little bit higher. The BPNN prediction model was time-consuming and prone to overfitting, so the SVR model is more suitable for the WMN throughput prediction.

Table 6 Fitting results of training set

Prediction model	BPNN	SVR
MSE	0.0278	0.0063
MAE	0.1184	0.0324

Table 7 Performance analysis of the WMN prediction

Prediction performance	BPNN	SVR
MSE	0.0755	0.0108
MAE	0.1587	0.0799
Prediction precision	0.9978	0.9985

5 Conclusion

A prediction model based on SVR for WMN throughput was proposed. The optimal parameters in SVR kernel function were confirmed by the grid-10-fold cross validation method. A WMN throughput prediction model was established based on SVR.

It verified the prediction accuracy of WMN throughput based on the SVR and the BPNN prediction models. The experimental results showed that the WMN throughput prediction accuracy based on SVR was slightly higher than that of the prediction model based on BPNN. The results of BPNN were not stable and have larger volatility. In the case where the number of samples was not enough, the prediction results of WMN throughput based on SVR were better than those predicted by BPNN prediction model. Through comparative analysis, the effectiveness and feasibility of SVR-based prediction model were testified.

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