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# Network Hotspot Prediction Model Based on GA-WRVM

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Abstract
In order to improve the prediction accuracy of hotspots events, this paper has proposed network hot events prediction model based on GA-WRVM. Firstly, a weighted coefficient is added to the noise variance of each sample data to get a WRVM, and then the combined kernel function is used to replace single kernel of RVM and kernel

parameters are optimized to establish prediction model using GA and finally, network hotspot data are used to make simulation and experiment analysis. The results show that, compared to neural networks and SVMs, GA-WRVM has reduced forecast error of network hot events, getting higher prediction accuracy of network hotspots, with stronger generalization ability.

Keywords: HOT EVENTS, COMBINED KERNEL FUNCTION, WRVM; GA

## 1. Introduction

Internet public opinion refers to certain social groups' views on some social issues within certain time, as well as the Internet users' reflection of the whole social opinion. As the network is featured by virtuality and openness, network public opinion has characteristics of substantively, abruptness and deviation, and users' umbrage encountered in work and life and their one-sided views on some issues can be vented through the network, and gray and negative comments on the network have adverse effects on social stability and public safety. Therefore, accurate and early prediction of the development trend of network hot events has important practical applications [1].

For prediction of network hot events, scholars have made exploration by putting a lot of time and effort. The traditional statistical theory prediction model is based on time series analysis and regression analysis and so on [2-4], and they all assume that development trend of network hot events is a linear variation, difficult to accurately grasp the developmental trend of network hot events, while the network hot events are affected by many factors, being a complex nonlinear system, the traditional method is difficult to establish accurate mathematical prediction model [5]. In recent years, machine-learning algorithms such as neural networks, support vector machines and others have received widespread attention, and achieved good predicting effect [6-8] in the network hotspot forecast. Neural network requires a lot of training samples, and when samples are limited, it has deficiencies such as poor ability to promote, difficult to determine the network structure, and slow convergence, etc.; based on structural risk minimization principle, support vector machine has overcome the defects of neural networks, and when there are less samples, better generalization ability can be got, but the error parameter must be set, and kernel function must satisfy Mercer conditions, and other weaknesses[9]. Based on the SVM, Tipping has proposed Relevance Vector Machine (RVM) in 2001, which integrates the advantages of Bayesian learning theory, and compared to SVM, RVM simply needs to set kernel parameters with kernel function no need to fulfill the Mercer conditions, and good results have achieved in aspects of fault diagnostics, network intrusion detection, image applications and so on [10, 11].

## 2. WRVM Prediction Model

### 2.1. RVM Model

For the training set: $\{\boldsymbol{x}_n, y_n\}_{n=1}^{N}$, $\boldsymbol{x}_n \in \boldsymbol{R}^d$, $y_n \in \boldsymbol{R}$, output of RVM is:

$$y(\boldsymbol{x},\boldsymbol{w}) = \sum_{i=1}^{N} w_i K(\boldsymbol{x},\boldsymbol{x}_i) + w_0 \tag{1}$$

In the formula, wi is the weight of model; N is the number of samples; K (x, xi) is core function.

RVM model structure is shown in Figure 1:

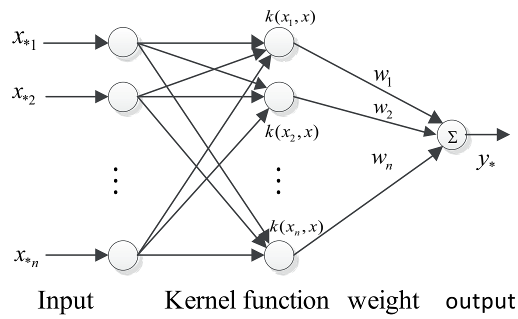


**Figure 1**. RVM model structure

The objective function is assumed to be independent, and comes from noise mode:

$$y_n = f(\boldsymbol{x}_n,\boldsymbol{w}) + \varepsilon_n \tag{2}$$

In the formula, εn is noise.

Likelihood function of training set is

$$p(y\,|\,w,\delta^2) = (2\pi\delta^2)^{-\frac{N}{2}} \exp\{-\frac{1}{2\delta^2}\|y-\Phi w\|^2\} \tag{3}$$

In the formula, $w=[w_1,w_2,\ldots,w_N]^T$; $\Phi=[\varphi(x_1),\ldots,\varphi(x_N)]^T$.

In order to avoid overfitting caused by the solution of optimal w using the maximum likelihood method, sparse Bayesian method is employed to endow weight w with priori conditional probability distribution:

$$p(w\,|\,\alpha) = \prod_{i=0}^{N} N(w_i\,|\,0,\alpha_i^{-1}) \tag{4}$$

According to Bayesian formula, the posterior formula of all the unknown parameters is as follows:

$$p(w,\alpha,\delta^2\,|\,y) = \frac{p(y\,|\,w,\alpha,\delta^2)p(w,\alpha,\delta^2)}{p(y)} \tag{5}$$

The posterior probability of the weight w can be expressed as:

$$p(w\,|\,y,\alpha,\delta^2)=\frac{p(y\,|\,w,\delta^2)p(w\,|\,\alpha)}{p(y\,|\,\alpha,\delta^2)}$$
$$=(2\pi)^{-\frac{(N+1)}{2}}|\Sigma|^{-\frac{1}{2}}\exp\{-\frac{1}{2}(w-\mu)^T\Sigma^{-1}(w-\mu)\} \quad (6)$$

In the formula, $\Sigma=(\delta^2\Phi^T\Phi+A)^{-1}$; $A=\mathrm{diag}(a_0,a_1,\ldots,a_N)$; $\mu=\delta^2\Sigma\Phi^Ty$.

Delta function is used to conduct approximate calculation, and the correlation vector learning is transformed to the quest of hyper-parameter posterior mode parameters, that maximization of a is $p(\boldsymbol{\alpha},\delta^2\,|\,\boldsymbol{y})\propto p(\boldsymbol{y}\,|\,\boldsymbol{\alpha},\delta^2)p(\boldsymbol{\alpha})p(\delta^2)$. Peak ofdelta function is used to approximate hyper-parameter posterior. When the prior situationis in the same condition, we just need to take the maximum value of $p(\boldsymbol{y}\,|\,\boldsymbol{\alpha},\delta^2)$, namely

$$p(y\,|\,\alpha,\delta^2)=\int p(y\,|\,w,\delta^2)p(w\,|\,\alpha)dw$$
$$=(2\pi)^{-\frac{N}{2}}\,|\,\delta^2I+\Phi A^{-1}\Phi^T\,|^{-\frac{1}{2}}\bullet\exp\{-\frac{1}{2}y^T(\delta^2I+\Phi A^{-1}\Phi^T)^{-1}y\} \quad (7)$$

It is obtained after using iterative estimation method repeatedly

$$\alpha_i^{new}=\frac{\gamma_i}{\mu_i^2} \quad (8)$$

$$(\delta^2)^{new}=\frac{\|y-\Phi\mu\|}{N-\Sigma_i\gamma_i} \quad (9)$$

In the formula, N is the number of sample data; μi is i-th posteriori average weight; γi = 1-Σij; Σij is the i-th diagonal element.

Learning process of RVM is the repeated iterative update of $\alpha_i^{new}$ and $(\delta^2)^{new}$ in formula (8) and (9), and Σ and μ are constantly updated at the same time until the convergence requirements are met. As can be seen from the calculation, with the increase in the number of iterations, most ai will tend to infinity, while the corresponding $w_i$ will tend to zero, so that most items of kernel matrix do not participate in the actual forecast calculation, implementing the model thinning.

**2.2. WRVM**

Assuming the noise εn of RVM training samples complies with Gauss distribution of mean 0 and variance $\delta^2$, but because of many factors affecting the network hot events, the sample data are difficult not to satisfy this assumption. Therefore, this paper adds a weighting factor for the noise variance of each sample data, and proposes weighted relevance vector machine (WRVM). The noise $\varepsilon_i$ contained in the i-th sample data is distributed as:

$$p(\varepsilon_i)=N(\varepsilon_i\,|\,0,\frac{\delta^2}{\beta_i}) \quad (10)$$

In the formula, $\beta_i$ is the added weight factor.

It is defined vector β = [β1, ..., βN] $^T$, and the likelihood function (3) of training set becomes:

$$p(y\,|\,w,\beta,\delta^2)=(2\pi\delta^2)^{-\frac{N}{2}}|B|^{\frac{1}{2}}\times\exp\{-\frac{1}{2\delta^2}(y-\Phi w)^TB(y-\Phi w)\} \quad (11)$$

In the formula, $B=\mathrm{diag}(\beta_1,\beta_2,\ldots,\beta_N)$.

Combining formula (4) and (6), it can be changed and obtained:

$$p(w\,|\,y,\alpha,\beta,\delta^2)=\frac{p(y\,|\,w,\beta,\delta^2)p(w\,|\,\alpha)}{p(y\,|\,\alpha,\beta,\delta^2)}=N(w\,|\,\Sigma,\mu) \quad (12)$$

In the formula, formulas of Σ and μ are respectively changed into:

$$\Sigma=(\delta^{-2}\Phi^TB\Phi+A)^{-1} \quad (13)$$

$$\mu=\delta^{-2}\Sigma\Phi^TBy \quad (14)$$

According to the conventional derivation process of RVM, it is ultimately got that:

$$\alpha_i^{new}=\frac{\gamma_i}{\mu_i^2} \quad (15)$$

$$\beta_i=2a_i+1/[2b_i+\delta^{-2}(y_i-\phi(x_i)^T\mu)^2+\delta^{-2}tr(\Sigma\phi(x_i)\phi(x_i)^T)^2] \quad (16)$$

$$(\delta^2)^{new}=\frac{(y-\Phi\mu)^TB(y-\Phi\mu)}{N-\Sigma_i\gamma_i} \quad (17)$$

In the formula, tr (·) denotes the trace of a matrix.

Equation (16) shows that with the increase in predictionsquare-error $(y_i-\phi(\boldsymbol{x}_i)^T\boldsymbol{\mu})^2$ in sample point, βi decreases and when βi is smaller, the contribution rate of Σ and μ declines. Therefore, when a prediction error of sample data islarger, its impact on the model will decrease with decrease in βi, so that robustness of RVM model is improved.

**2.3. Training steps of WRVM**

Step1: Initialize the parameters of α, β, $\delta^2$, $a_i$ and *b* in model.

Step2: Calculate the posterior covariance Σand mean μ of the weight W using (13) and (14).

Step3: Use formula (15) to (17) calculates update hyper-parameters $\alpha_i^{new}$, $\beta_i$ and $(\delta^2)^{new}$.

Step4: Determine all parameters whether the convergence conditions are met, if met, then stop iterative computation; if not satisfied, return Step2.

**3. Network Hot Events Prediction Model Based on WRVM**

**3.1. Combined Kernel Function and Parameter Optimization**

The basic idea of combined kernel function is to synthesize advantages of different kernel functions and to combine a plurality of different kernel functions to expect that the combined kernel function has better characteristics, and polynomial kernel $K_{poly}$ is a global kernel function, while Gaussian kernel $K_{RBF}$ function is a local kernel function. Therefore, combined kernel function of WRVM in this paper is:

$$K = \lambda K_{poly} + (1-\lambda) K_{RBF} \tag{18}$$

In the formula, λ is a mixed weighting coefficient.

Polynomial kernel function$K_{poly}$ and Gaussian kernel $K_{RBF}$ are defined as follows:

$$\begin{cases} K_{poly} = [(x \cdot x_i) + 1]^d \\ K_{RBF} = \exp(-\dfrac{\|x - x_i\|^2}{2\delta^2}) \end{cases} \tag{19}$$

Combined kernel function parameters of WRVM mainly have the weight coefficient λ, polynomial kernel parameter d and Gaussian kernel radius δ, and in order to obtain better network hotspots prediction model, the parameters of WRVM are optimized using genetic algorithm.

**3.2. Working Steps of GA-WRVM**

(1) Collect historical data of network hot events, and conduct corresponding pretreatment of the data.

(2) Divide the collected historical data into training set and test set used for learning and modeling of GA-WRVM.

(3) Input the training set to WRVM to learn, and optimize WRVM parameters using GA (mixing weight coefficient λ, polynomial kernel parameter d and Gaussian kernel function radius δ).

(4) Establish networking hot events prediction model on the basis of optimized WRVM (mixing weight coefficient λ, polynomial kernel parameter d and Gaussian kernel function radius δ).

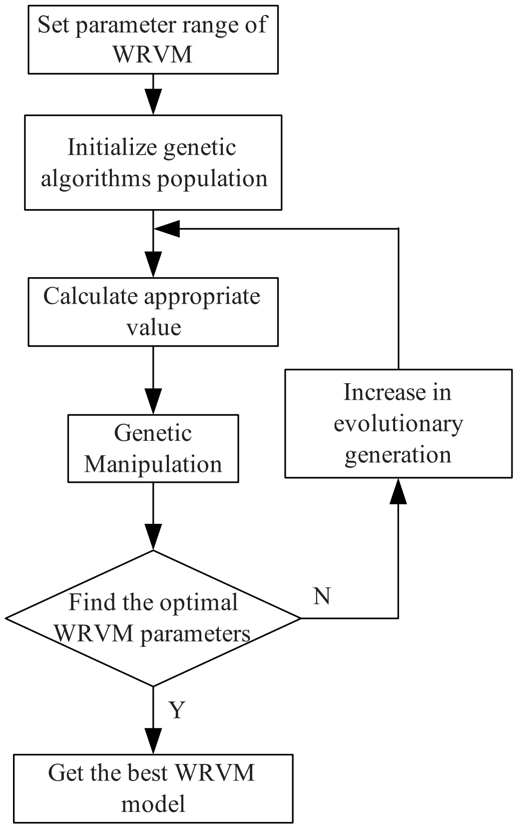


**Figure 2.** Flowchart of GA in optimization of WRVM parameters

(5) Test the test set according to the established model, and predict network hot events at some point in the future.

**4. Simulation Experiment**

**4.1. Data sources**

In environment of P4 3.0G CPU, 4G RAM, Windows 7, algorithm is achieved through Matlab 2012 programming. "Cousin's dismissal" is selected as the network hot source event, and the forum data in Tianya are selected as data sources of network hotspots, specifically shown in Figure 3. The first 30 data are taken as training samples, used for training of predictive model; 20 data are taken as the test sample, used for testing the training effect of prediction model.

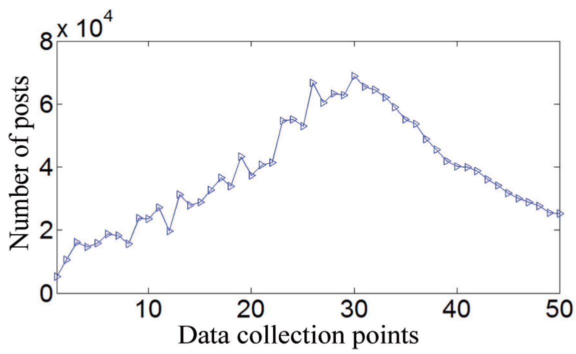


**Figure 3.** Historical events of "cousin's dismissal"

**4.2. Data Preprocessing**

Because hotspots event value ranges vary greatly, in order to avoid large numbers “swallowing up” small numbers, training speed is accelerated, and data are normalized, and the normalization formula is:

$$y' = \frac{y - y_{\min}}{y_{\max} - y_{\min}} \times 0.8 + 0.1 \qquad (20)$$

In the formula, y, $y_{min}$ and $y_{max}$ represent sample data, the minimum and maximum sample data in the sample data respectively; is the normalized data.

**4.3. Construction of Learning Samples**

Network hotspot data is a typical time-series, featured by time-lag and aftereffect, and that is, the number of posts currently is closely related to the number of posts some time ago, thus the historical number of network hotspots can be considered as vector input of network hotspots at present, and then how many historical number of posts can impact network hotspots change at present on earth is determined in the paper by FNN method, and the results are shown in Figure 4.

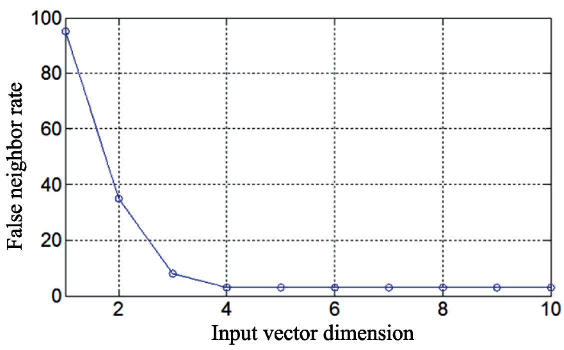


**Figure 4**. Identified input vector dimension of network hotspots

Figure 4 shows that when the input vector dimension = 4, there is no change or quite small rangeability in the neighbor rate, which indicates the number of posts at the former four time points is taken as the input vector (x) of model; the number of posts of network hotspots at the current time points is taken as the corresponding expected output (y), and then the normalized model learning samples are shown in Table 1.

**4.4. Contrast Model**

ARIMA, BPNN, $K_{poly}$–RVM and $K_{RBF}$–RVM are employed as comparative models, and RMSE and MPAE are used as evaluation criteria, specifically shown as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \qquad (21)$$

**Table 1.** Constructed model learning sample

| Input vector (x) | | | | Output vector |
|---|---|---|---|---|
| 0.079 | 0.158 | 0.251 | 0.225 | 0.255 |
| 0.158 | 0.251 | 0.225 | 0.255 | 0.289 |
| 0.251 | 0.225 | 0.255 | 0.289 | 0.285 |
| 0.225 | 0.255 | 0.289 | 0.285 | 0.244 |
| 0.255 | 0.289 | 0.285 | 0.244 | 0.356 |
| 0.289 | 0.285 | 0.244 | 0.356 | 0.366 |
| 0.285 | 0.244 | 0.356 | 0.366 | 0.413 |
| 0.244 | 0.356 | 0.366 | 0.413 | 0.292 |
| 0.356 | 0.366 | 0.413 | 0.292 | 0.474 |
| 0.366 | 0.413 | 0.292 | 0.474 | 0.418 |
| 0.413 | 0.292 | 0.474 | 0.418 | 0.442 |
| 0.292 | 0.474 | 0.418 | 0.442 | 0.490 |
| 0.474 | 0.418 | 0.442 | 0.490 | 0.542 |
| 0.418 | 0.442 | 0.490 | 0.542 | 0.527 |
| … | … | … | … | … |
| 0.458 | 0.434 | 0.433 | 0.399 | 0.385 |

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{(y_t - \hat{y}_t)}{y_t}\right| \times 100\% \qquad (22)$$

In the formula, $y_t$ and $\hat{y}_t$ are the actual value and the predictive value of the model respectively, and n is the number of samples.

**4.5. Result and Analysis**

**4.5.1. Single-step Predictive Performance Analysis**

Firstly, 30 data are employed for training, and modeling and prediction are conducted for the 31th data point, and then the 31th data point is added to the training set, and modeling and prediction are conducted for the 32th data point, and the like. Then single-step predictive value of 20 test sets are obtained, and forecasted results of network hot events for different models are shown in Figure 5. Predicted results of RMSE and MAPE are shown in Table 2.

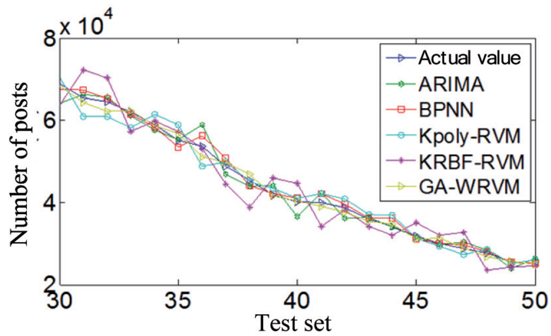


**Figure 5.** Single-step forecasted results of “cousin’s dismissal” event

Analyzing the results in Table 1 and Figure 5, we can get the following conclusions:

**Table 2.** Comparison of single-step prediction performance for each model

| Model | *RMSE* | *MAPE* |
|---|---|---|
| ARIMA | 1749.026 | 8.37% |
| BPNN | 1705.251 | 6.15% |
| $K_{poly}$-RVM | 1957.875 | 5.83% |
| $K_{RBF}$-RVM | 3522.680 | 4.30% |
| GA-WRVM | 897.302 | 2.75% |

**Table 3**. Comparison of multistep prediction performance for each model

| Prediction Model | *RMSE* | *MAPE* |
|---|---|---|
| ARIMA | 3525.616 | 16.36% |
| BPNN | 3380.586 | 13.97% |
| $K_{poly}$-RVM | 3301.426 | 12.45% |
| $K_{RBF}$-RVM | 2987.123 | 13.52% |
| GA-WRVM | 1496.820 | 7.33% |

(1) Compared to the ARIMA, GA-WRVM has better prediction performance of network hot events, suggesting that GA-WRM overcoming ARIMA can only describe linear change and cyclical changing characteristics of network hot events, with good nonlinear predictive ability.

(2) Compared to the BPNN, GA-WRVM has more accurate and reliable predictions, suggesting that GA-WRVM can avoid slow convergence of BPNN, and for small samples of hot data network, it has stronger ability to promote, which has improved forecast accuracy of network hot events.

(3) Compared to single function of $K_{poly}$-RVM and $K_{RBF}$-RVM, GA-WRVM has fairly well anastomotic predicted values and actual values, and the prediction error is significantly lower than that of the single kernel function, able to achieve the desired effect of prediction, suggesting that GA-WRVM combines global function and local function together, so as to further tap the dynamic change information implicit in network hotspot data and to predict more reliable results.

**4.5.2. Multi-step Predictive Performance Analysis**

Network hotspot prediction generally requires a large amount of initial lead, and the use of single-step prediction cannot make a timely response to negative network hot events. Therefore, to achieve multistep prediction for network hot events using iterative method, multistep forecasted results of the three-step ahead are obtained, as shown in Figure 6, and the predicted results of RMSE and MAPE are shown in Table 3.

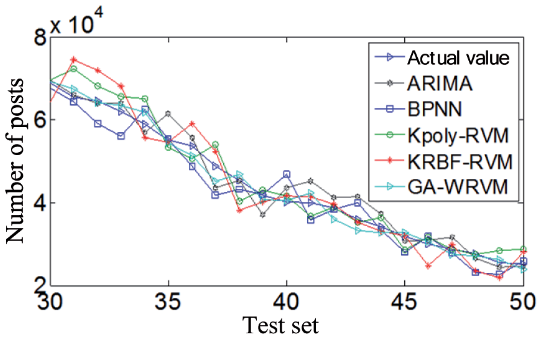


**Figure 6**. Multi-step forecasted results of "cousin's dismissal" event

From Table 3 and Figure 6, ARIMA, BPNN, $K_{poly}$-RVM and $K_{RBF}$-RVM have great error in multistep prediction, exceeding the permissible range (less than 10%) of error in practical application, and GA-WRVM prediction error is obviously in the permissible range of error in practical application, with better grasp of changing situation of network hot events, and wider range of applications.

**4.5.3. Prediction of other Network Hot Events**

To test the versatility of GA-WRVM, single-step prediction has been conducted by choosing the hottest network events in 2013 such as "Lankao fire", "mark-reducing of running yellow lights", "group licentiousness event in Rendez-Vous", "Ministry of Railways, a thing of the past" and "neck-choke of city management in Guangzhou", and the errors of the forecasted results are shown in Table 4. From Table 4, the GA-WRVM prediction error is relatively small, a network hot event model with better versatility.

**Table 4**. Single-step prediction error of GA-WRVM for other network hot events

| Hot Events | *RMSE* | *MAPE* |
|---|---|---|
| Lankao fire | 855.165 | 2.90% |
| Mark-reducing of running yellow lights | 949.463 | 3.69% |
| Group licentiousness event in Rendez-Vous | 881.923 | 2.75% |
| Ministry of Railways, a thing of the past | 931.341 | 3.84% |
| Neck-choke of city management in Guangzhou | 1240.021 | 4.92% |

**Conclusions**

Network hot event is a complex variation system, and in order to improve its forecast accuracy, this paper has proposed network hot events prediction model based on GA- WRVM. Firstly, by constructing combined kernel function to replace single kernel function, and then nuclear parameters are optimized using GA with strong global search capability, and finally simulation test is conducted by using historical data of network hot events. The results show that:

compared to RVM model of single kernel function, GA-WRVM has evidently decreased prediction error. Compared to other common prediction models of network hot events, GA-WRVM have greater generalization and higher prediction accuracy, able to better fit the situation changes in the system network hot events, and the predicted results help to correctly grasp the development of network hot spots and to promote the implementation of building a harmonious society.

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# WSN Maximum Lifetime Combining the Heuristics Based on pERPMT

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Abstract
On account of issues such as low lifetime of WSN resulted from battery capacity limitations of sensor nodes, this paper has proposed WSN maximum lifetime algorithm combining improved heuristic method based on pERPMT. Firstly, each sensor node is initialized by heuristics, and the node energy is divided into the origin data of sensor nodes and delayed data of other nodes. Then an added preferred measure is used to delay energy consumption of one-hop node. Finally, according to the average energy of path, a priority is distributed for each routing to achieve the ultimate optimization of WSN through pERPMT. Experiments with different distribution patterns and network lifetime have verified the validity and reliability of the proposed method, and the experimental results show that compared to more advanced heuristic ERPMT-CMAX and ERPMT-OML, the proposed algorithm has significantly increased the coverage of WSN, and greatly extended the life of the network.
Keywords: WSN, MAXIMUM LIFETIME, HEURISTICS, ROUTING ENERGY MANAGEMENT, PRIORITY ROUTING ALGORITHM

**Introduction**

In recent years, improvements in Nano-Electromechanical System (NEMS) [1] have paved the new applications path of WSN [2,3]. WSN comprise a large number of small nodes, having capabilities of sensing, computing and wireless communication [4]. However, the battery capacity of sensor nodes is limited, resulting in its limited lifetime, and many researchers are to maximize the life of the sensor nodes through the development of new routing technologies. There-