Green Energy Forecast Based on Improved Grey Model for Green Base Stations

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Abstract. With the increasing scale of mobile network, the proportion of energy consumption of network in global is rapidly growing. Particularly, in order to estimate available energy in each node to intelligently optimize the base station by combining with the state of load, an improved grey model is put forward for green energy forecast in smart green base station (GBS), so that the smart GBS can be self-sufficient in energy under the premise of ensuring the quality of communication. In the paper, according to the weather conditions in a certain region, and combined with the solar energy harvesting system, the energy harvesting trend can be forecasted from an improved grey model which based on grey system, and then compared with the real data to prove the validity and practicability of the model.

Keywords: Smart green base station · Green energy · Energy harvesting system · Grey model · Solar energy

1 Introduction

Current research on green base station (GBS) mainly focuses on the power consumption and energy efficiency. Literature [1] puts forward to selectively close the base station with low traffic volume to reduce the energy consumption, but the base station will be accompanied by the emergence of the coverage of the problem. To solve this problem, The method of cell scaling is presented by paper [1, 2] which can dynamically adjust the coverage area of the cell to achieve the reasonable utilization of the system resources according to the network and load conditions, and also prove that the reasonable cell scaling scheme is an effective green access scheme. The power consumption of base station is divided into the static power consumption of the system and the dynamic network energy consumption in Ref. [3], and the optimal scheme is given in the time domain, spatial domain and frequency domain respectively as well. Paper [4] proposes a kind of energy saving mechanism in the case of limited battery capacity from the perspective of information theory. Further, in the case of limited battery capacity, paper [5] consider the dynamic energy arrival queue as a binary time channel without noise, and then puts forward an auxiliary random variable save-and-transmit scheme by

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combining Anantharam–Verdu's bits through queues and Shannon's state-dependent channels with causal state information available at the transmitter. Reference [6, 7] present that the directional glue-pouring algorithm is the optimal scheme for offline energy management for throughput maximization. Literature [8] puts forward a data packet transmission model associated random importance value for online energy management for general reward maximization. In the case of clear known of the battery status, the paper [9] presents a great potential energy saving method is Markov Decision Processes. In addition, energy efficiency optimization can be calculated through Policy Iteration Algorithm or some Heuristics Algorithm in Reference [10]. For the case of unknown battery status, the authors in [10] proposes the above methods are no longer probation, but some suboptimal policies can be obtained under the condition of full acknowledge of the past history of harvesting status. Besides, based on practical implement of solar energy as energy supply for base station, Literature [11] demonstrates the feasibility of full GBS.

In summary, GBS optimization is mainly limited in energy saving and energy efficiency improvement in the past, or based on the model which require to fully acquire the battery or energy harvesting statues in advance. Yet it only can find some rough suboptimal policies without known the energy status. As a whole, it is especially meaningful to fully acquire the development trend of energy status to do some forward prediction and then to do related forward optimization.

In this paper, a forecast algorithm based on an improved grey model (GM) of energy harvesting is proposed in the GBS with the supply energy of solar to forecast the energy trend to dynamically optimize the network to fulfill the energy supply of GBS itself under the condition of ensuring the quality of communication.

2 Network Models

With the continuous development of green base station technology, the future green wireless networks will become reality, as shown in Fig. 1, is a kind of future green wireless networks scenario. The model uses hierarchical management architecture. There are a number of micro GBS in a macro GBS, and also there are several green relay station as the supplementary of some micro GBS.

By selecting optimization strategy intelligently which based on status and trend of the energy and load of network, Resource Management Center's main function is to ensure the network's robustness, and to achieve energy saving and energy efficiency. And so as to other Resource Manager. The model is shown in Fig. 2. In architecture of this scenario, the green energy (GE) supply system refers to the solar power supply module. GE management system is mainly responsible for the monitoring and forecasting of the energy state of the solar power supply module, which provides reference for the intelligent strategy selection system. Control System is mainly responsible for monitoring the change of strategy so as to apply the new strategy through the network management system to the network to achieve the purpose of control network. Network management system is mainly responsible for monitoring and prediction of the network state, which provides reference function for monitoring and forecasting of network

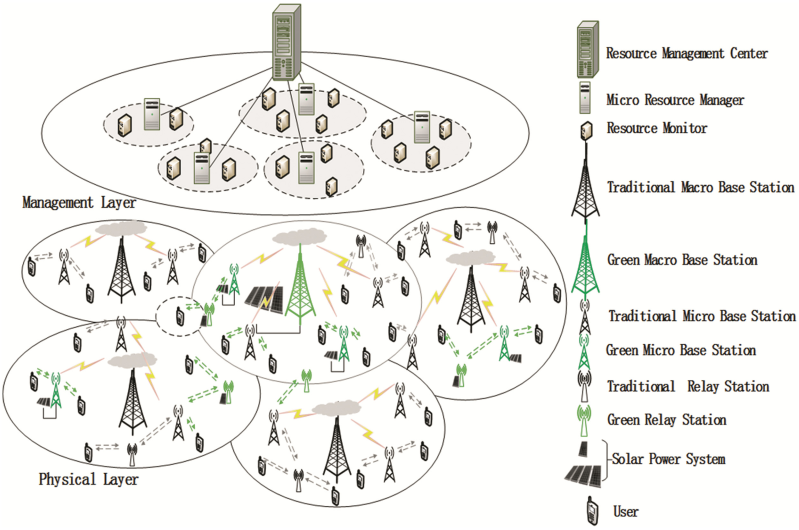

Fig. 1. Future wireless network with green base stations (Color figure online)

energy consumption, and provides the control interface to control the consumption status and forecast function, which provide reference function for strategy evaluation system and intelligent strategy selection system. The strategy evaluation mechanism is automatically completed by the corresponding algorithm. Strategy optimization mechanism can be machine learning, artificial intelligence, and also human analysis. Based on the state and forecast function of GE and network energy consumption, strategy storage system responsible for storage and management of the strategy. Intelligent strategy selection system responsible for choosing the best strategy from strategy storage system for control system.

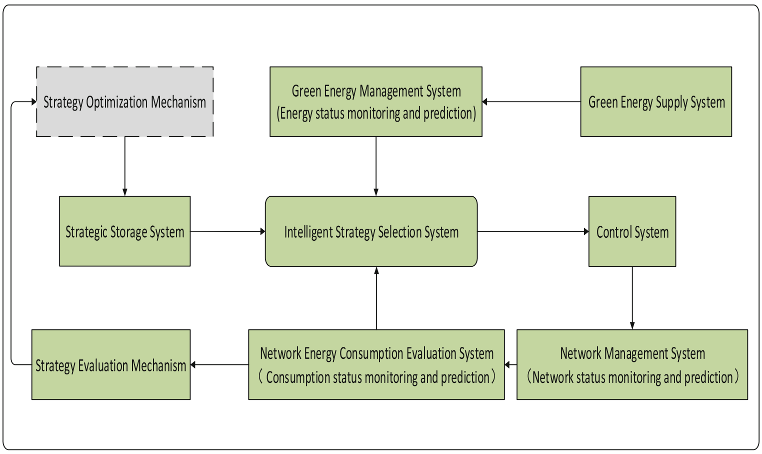

Fig. 2. Resource management model

Usually, the network optimization strategy is different under different circumstances. The optimization strategies of energy harvesting based on energy harvesting in various scenarios, such as Markov Decision Processes, queuing theory, information theory, water injection algorithm, etc., are summarized in paper [10]. However, the energy consumption function of the network obtained by energy consumption evaluation system must be matched with the energy state function obtained by the GE management system, as shown in Fig. 3.

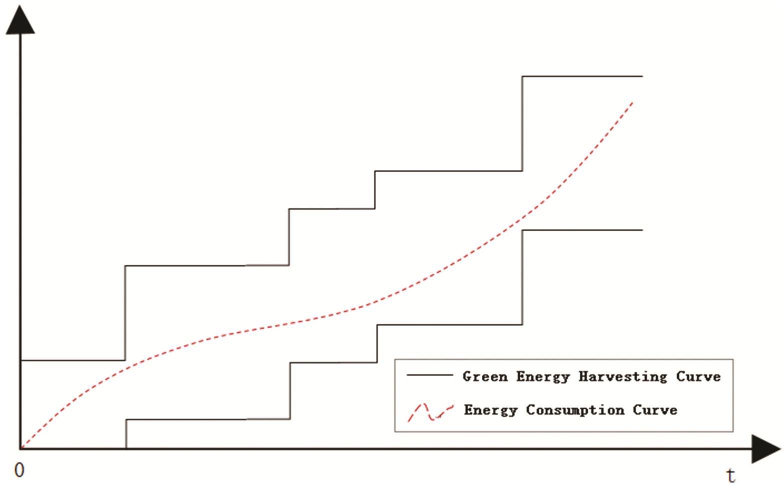

Fig. 3. Constrained energy consumption model

3 Green Energy Forecast

Solar energy is influenced by light intensity and temperature. The algorithm is improved as follow. Firstly, the primary data is processed by smooth processing equation. Secondly forecast model is built by using grey system. Thirdly, it will correct the forecast deviation through residual correction based on cosine function and then find the sequence rules through periodic extension for residual corrected sequence. Finally, in order to obtain the performance of the model, the log data are predicted so that it can be compared with the real data.

3.1 Smoothing Process of Primary Sequence

A primary time sequence as follow:

$$x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)],\ n \geq 4 \tag{1}$$

Smooth processing equation as follow:

$$\tilde{x}^{(0)}(k) = \frac{x^{(0)}(k-1) + 2x^{(0)}(k) + x^{(0)}(k+1)}{4},\ k = 1, 2, \cdots, m \tag{2}$$

Specifically, the beginning and end of the sequence can be calculated as follow:

$$\tilde{x}^{(0)}(1) = \frac{3x^{(0)}(1) + x^{(0)}(2)}{4},\ \tilde{x}^{(0)}(m) = \frac{x^{(0)}(m-1) + 3x^{(0)}(m)}{4} \tag{3}$$

In (3), m is the number of raw data sequence, and then the forecast number of sequence is $n - m + 1$. The purpose of smoothing is to reduce the number of data mutations caused by the subjectivity and contingency, thereby reduce the interference.

3.2 Grey Forecasting Model

Applying Accumulating Generation Operator (AGO) to the input sequence $x^{(0)}$, a new sequence is generated as follow:

$$x^{(1)} = [x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(m)],\ n \geq 4 \tag{4}$$

Where

$$x^{(1)}(k) = \sum_{i=1}^{k} \tilde{x}^{(0)}(i),\ i = 1, 2, \cdots, m \tag{5}$$

Assuming the albinism differential equation of $x^{(1)}(k)$ as follow:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \tag{6}$$

Where, a is the development parameters of the model, and reflect the development trend of $x^{(1)}$ and the original sequence, u is the model coordination coefficient, and reflect the transformation relationship between data. Assuming $P = \begin{pmatrix} a \\ u \end{pmatrix}$, and according to the least square method, we can get the equation as follow:

$$P = (Q^T Q)^{-1} Q^T H \tag{7}$$

Where

$$H = \begin{pmatrix} x^{(0)}(2) \\ \vdots \\ x^{(0)}(m) \end{pmatrix};\ Q = \begin{pmatrix} -\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}[x^{(1)}(m-1) + x^{(1)}(m)] & 1 \end{pmatrix} \tag{8}$$

The solution of (6) is an exponential function and the initial condition for $x^{(1)}(1)$ is $x^{(1)}(1) = \tilde{x}^{(0)}(1)$. Then, $x^{(1)}(k+1)$ can be obtained for $k = 1, 2, \cdots, m$ as follow:

$$x^{(1)}(k+1) = [\tilde{x}^{(0)}(1) - \frac{u}{a}]e^{-ak} + \frac{u}{a} \tag{9}$$

Prediction model can be obtained through accumulated subtraction operation on original series $x^{(0)}$ as follow:

$$\hat{x}^{(0)}(k) = (1 - e^{a})(\tilde{x}^{(0)}(1) - \frac{u}{a})e^{-a(k-1)} \tag{10}$$

Fitting sequence of the original sequence $\hat{x}^{(0)}$ is obtained when $k = 1, 2, \cdots, m$, and the forecasted sequence is derived when $k = m + 1, m + 2, \cdots, n$.

3.3 Residual Correction Based on Cosine Function

Usually, the positive and negative residual of primary sequence alternately appear in the model that result in the deviation of model. However, the residual can be compensated by using the periodicity of cosine function, and the residual correction function is defined as follow:

$$\begin{cases} \delta_1^{(i)} = \cos(2\pi \times \frac{i}{n}) \\ \delta_2^{(i)} = \cos(4\pi \times \frac{i}{n}) \\ \vdots \\ \delta_k^{(i)} = \cos(2k\pi \times \frac{i}{n}) \end{cases} \quad (i = 0, 1, 2, \cdots, n) \tag{11}$$

Where, i is the location of correcting data, and δ_k is the corresponding correction function, k is the length of correction sequence. Correction function can effectively improve the accuracy of forecasted sequence through a larger k, but, with the increasing of k, the amount of calculation increases rapidly as well. So it necessary to choice an appropriate k.

The residual value is calculated as follow:

$$\delta(i) = \hat{x}^{(0)}(i) - x^{(0)}(0),\ i = 1, 2, \cdots, m \tag{12}$$

Assuming that the residual value of each data of forecasted sequence can be expressed by the correction function, and then we get the function as follow:

$$\begin{cases} \hat{\delta}(1) = \lambda_1\delta_1^{(1)} + \lambda_2\delta_2^{(1)} + \cdots + \lambda_i\delta_i^{(1)} \\ \hat{\delta}(2) = \lambda_1\delta_1^{(2)} + \lambda_2\delta_2^{(2)} + \cdots + \lambda_i\delta_i^{(2)} \\ \vdots \\ \hat{\delta}(m) = \lambda_1\delta_1^{(m)} + \lambda_2\delta_2^{(m)} + \cdots + \lambda_i\delta_i^{(m)} \end{cases} \tag{13}$$

And then

$$\widehat{\delta} = \lambda\Delta = \{\lambda_1, \lambda_2, \cdots, \lambda_k\}\begin{Bmatrix} \cos(2\pi \times \frac{1}{n}), \cos(2\pi \times \frac{2}{n}), \cdots, \cos(2\pi \times \frac{i}{n}) \\ \cos(4\pi \times \frac{1}{n}), \cos(4\pi \times \frac{2}{n}), \cdots, \cos(4\pi \times \frac{i}{n}) \\ \vdots \\ \cos(2k\pi \times \frac{1}{n}), \cos(2k\pi \times \frac{2}{n}), \cdots, \cos(2k\pi \times \frac{i}{n}) \end{Bmatrix} \tag{14}$$

Generally, (14) is no solution, but based on the minimum squared error of primary residual and corrected residual, the solution can be found by using least square method as follow:

$$\lambda = (\Delta^T \Delta)^{-1} \Delta^T \delta \tag{15}$$

And (15) is restricted by the condition as follow:

$$\min[\widehat{\delta}(i) - \delta(i)]^2 \tag{16}$$

So the fitted value of residual is obtained as follow:

$$\widehat{\delta}(i) = \lambda_1 \delta_1^{(i)} + \lambda_2 \delta_2^{(i)} + \cdots + \lambda_k \delta_k^{(i)} \tag{17}$$

Finally, the residual correction of original forecast based on cosine function is derived as follow:

$$\hat{x}^{(0)}(k) = \hat{x}^{(0)}(k) + \widehat{\delta} \tag{18}$$

3.4 Periodic Extension for Residual Correction Sequence

Aimed at digging out the rules hided in data and much more closing to real data, a new method that applies the periodic extension to the forecast result which has been through residual correction by cosine function is put forward in this section, and specific method is as follows.

Step 1: Obtaining deviation,

$$x'(k) = \tilde{x}^{(0)} - \hat{x}(k) \tag{19}$$

Step 2: Calculating the mean generating function of $x'(k)$ by using (20),

$$\bar{x}_l(i) = (\sum_{j=0}^{m_l-1} x'(i + jl))/m_l,\ i = 1, 2, \cdots, l,\ 1 \le l \le L \tag{20}$$

Where, m is the length of smooth processed sample sequence, $m_l = [m/l]$ is the maximum integer which is less than m/l, and $L = [m/2]$ is the same, so mean generating function is calculated as follow:

$$\begin{Bmatrix} \bar{x}_1(1) & \bar{x}_2(1) & \bar{x}_3(1) & \cdots & \bar{x}_L(1) \\ & \bar{x}_2(2) & \bar{x}_3(2) & \cdots & \bar{x}_L(2) \\ & & \bar{x}_3(3) & \cdots & \bar{x}_L(3) \\ & & & \ddots & \vdots \\ & & & & \bar{x}_L(L) \end{Bmatrix} \tag{21}$$

And $f_l(k)$, the periodic extension function of $\bar{x}_l(i)$, is derived by using the method as follow:

$$f_l(k) = \bar{x}_l(k),\ k = i[\mathrm{mod}(l)],\ k = 1, 2, \cdots, m \tag{22}$$

Step 3: Extraction advantage period,

According to the basic principle of analysis of variance, it can be detected whether or not these is period l hiding in $x'(k)$ by the function as follow:

$$F^{(l)} = (m - l)S^{(l)}/((l - 1)S) \tag{23}$$

Where

$$S^{(l)} = \sum_{i=1}^{l} m_i(\bar{x}_l(i) - \bar{x})^2,\ m_i = m/i,\ \bar{x} = (\sum_{i=1}^{M} x(i))/m \tag{24}$$

$$S = \sum_{i=1}^{l} \sum_{j=1}^{m} (x(i + (j - 1)l) - \bar{x}_l(i))^2 \tag{25}$$

Equation (23) is satisfied with the distribution of F with the freedom $(l - 1, m - l)$. For a given confidence level in advance, if $F^l > F_\alpha(l - 1, m - l)$, it can be confirmed that l is the distinct period of $x(k)$.

Step 4: Acquisition periodic deviation correction sequence $x''(k)$, the periodic deviation correction sequence, is defined as follow:

$$x''(k) = x'(k) - f_l(k) \tag{26}$$

By repeating step 3 and step 4 for $x''(k)$, more obscure sequence rules will be found.

Step 5: The final forecast based on periodic deviation correction,

The value of the same time in different periods is superimposed as:

$$f(k) = \sum_{i=1}^{l} f_i(k) \tag{27}$$

Approximately, $x'(k)$ can be taken by $f(k)$, the final forecast result based on periodic deviation correction is obtained as follow:

$$\bar{x}(k) = \hat{x}(k) + f(k) \tag{28}$$

4 Simulation and Analysis

In order to obtain the improved grey model, the primary GM is processed by two consecutive steps that one is named as residual correction based on cosine function and the follow is periodic extension for residual correction sequence, which had discussed above. The main task of this section is the simulation of the improved model and then discussing the results.

Experimental data, coming from a polycrystalline silicon solar panel with 50 W power and 20 V open circuit voltage, is the record of current I of every 20 min for five days. For convenience, t is replaced with the number collection points.

On small scale, selecting 5 consecutive points of the first day to forecast the value of sixth points dynamically, and then repeating the process until all the points are predicted, finally, comparing with the real data of first days, as shown in Fig. 4.

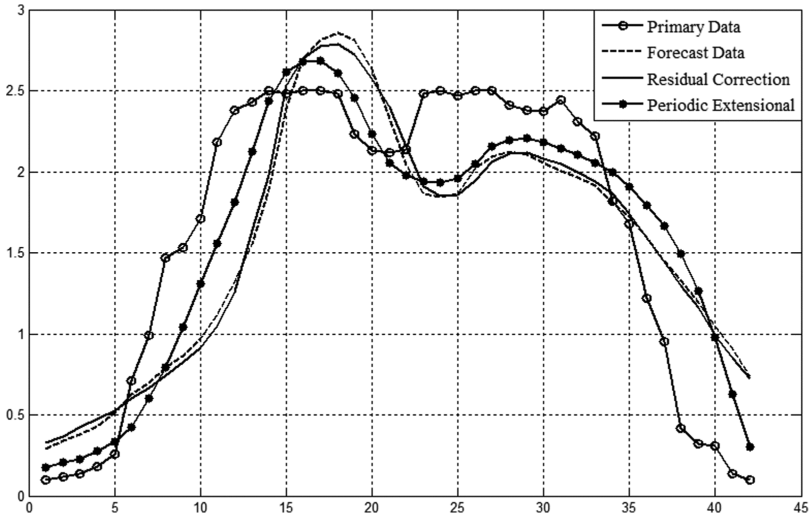

Fig. 4. Forecast results on small scale

The Primary Data curve is drawn out from the real data of first day. Forecast Data is the result of primary GM, obviously, not only the curve has a large fluctuation, but there are more bump point. Residual Correction curve, which is the residual correction result of forecast data curve based on cosine function, is very smooth. Periodic Extensional curve is the periodic extensional result of residual correction data, it makes the rules hided in data much clearer. There is no doubt that the improved grey model much more accurate.

The forecast results for next three days which based on the data of first five days is shown in Fig. 5.

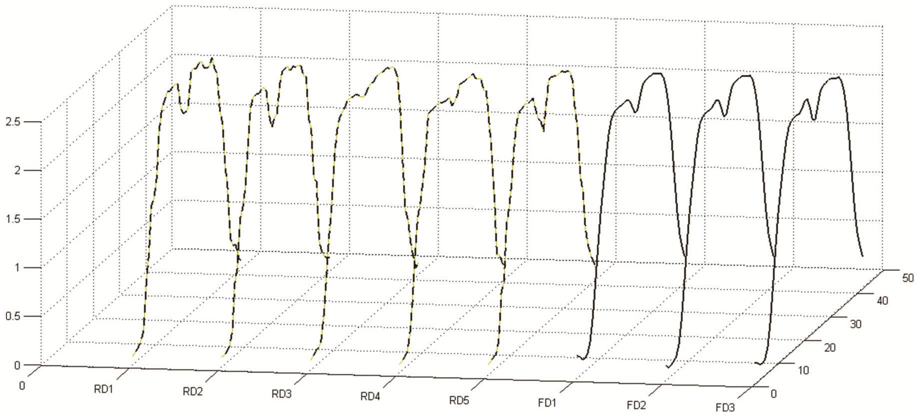

Fig. 5. Forecast results on large scale

RD1 to RD5 is the real data of the first five days and FD1 to FD3 is the forecast results of next three days. It obvious that the forecast results strongly depend on the original real data., though the shape of the forecast results of next three days are very similar to that of the original real data of first five days, it has its own feature as well, i.e. the forecast results above maintain the stability of the fixed points, and highlight the development trend of the unstable points. So it necessary to obtain more data to get much accurate forecast results.

In summary, by smoothing the primary data, correcting the residual of forecast result, and periodic extension of the correction result, the primary Gm is improved and it can weaken the deviation caused by the systematic and random error and highlight the regularity hided in data. Although the forecast results are slightly lagging, it is very close to the trend of development and total amount of the energy. On the other hand, the forecast results based on large scale and mass history data can meet the development and variation trend of the real data to some extent in the case of no obvious change of the external environment which both proved the outstanding performance of the model.

5 Conclusion

In this paper, we propose a full GBS model which depends on solar energy, and improve the accuracy of the forecast of solar energy by using an improved GM. The practice results show that the forecast data is highly close the real data in the absence of unexpected circumstances. However, this prediction is strongly dependent on real data. In order to improve the accuracy of forecasting results, the amount of sample data should be increased. In view of the model of the solar energy forecast, a more effective solution is to add the dynamic real-time forecast to the model, and then combine with the former forecast result based on former sample data to correct the deviation to improve the accuracy of the forecast dynamically. But the cost is an increase of the system overhead and energy consumption. So it is significance to make a comprehensive evaluation before the practical implement of the model for obtaining optimization.

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