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The Application of Genetic Algorithm in Power Short-term Load Forecasting

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Abstract. In the paper, an improved genetic algorithm is put forward to solve the problem of short-term load forecasting in power system. While Traditional forecasting model is not accurate and the value of parameter α is constant, the proposed algorithm could overcome these disadvantages. In order to construct optimal grey model to enhance the accuracy of forecasting, the improved decimal-code genetic algorithm (GA) is applied to search the optimal α value of grey model. What's more, this paper also proposes the one-point linearity arithmetical crossover, which can greatly improve the speed of crossover and mutation. Then, a comparison of the performance has been made between IGA and traditional forecasting model. Finally, a daily load forecasting example is used to test the IGA model. Results show that the GM(1,1)-IGA had better accuracy and practicality.

Keywords: Short-term Load Forecasting, Genetic Algorithm, One-point Linearity Arithmetical Crossover, GM (1, 1)

1. Introduction

Power short-term load forecasting (PSTLF) aims at predicting electric loads for a period of minutes, hours, days or weeks. The quality of the short-term load forecasts with lead times ranging from one hour to several days ahead has a significant impact on the efficiency of operation of any power utility, because many operational decisions, such as economic dispatch scheduling of the generating capacity, unit commitment, scheduling of fuel purchase as well as system security assessment are based on such forecasts [1]. Traditional short-term load forecasting models can be classified as time series models or regression models [2]-[4]. Several models such as expert systems and pattern recognition models [5]-[6] have also been developed.

Time series models employ the historical data for extrapolation to obtain the future hourly loads. The disadvantage of these models is that the load trend is stationary and that weather information or any other factors that contribute to the load behavior cannot be fully utilized. Usually, these techniques are effective for the forecasting of short-term load on normal days but fail to yield good results on those days with special events [7]-[9]. Furthermore, because of their complexities, enormous computational efforts are required to produce acceptable results.

Genetic algorithms (GA) were firstly described by John Holland, who presented them as an abstraction of biological evolution and gave a theoretical mathematical framework for adaptation .The distinguishing feature of a GA with respect to other function optimization techniques is that the search towards an optimum solution proceeds not by incremental changes to a single structure but by maintaining a population of solutions from which new structures are created using genetic operators[12].Usually, the binary representation was applied to many optimization problems, but in this paper genetic algorithms (GA) adopted improved decimal-code representation scheme.

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The GM(1,1) is the main model of grey theory of prediction, i.e. a single variable first order grey model, which is created with few data (four or more) and still we can get fine forecasting result [10]. The grey forecasting models are given by grey differential equations, which are groups of abnormal differential equations with variations in behavior parameters, or grey difference equations which are groups of abnormal difference equations with variations in structure, rather than the first-order differential equations or the difference equations in conventional cases [11]. The GM(1,1) has parameter α which was often set to 0.5 in many articles, and this constant α might not be optimal, because different questions might need different α value, which produces wrong results. In order to correct the above-mentioned defect, this paper attempts to estimate α by genetic algorithms.

The paper proposed GM(1,1)-connection improved genetic algorithm (GM(1,1)-IGA)to solve power short-term load forecasting (PSTLF) problems in power system. The traditional GM(1,1) forecasting model often sets the coefficient α to 0.5, which is the reason why the background value $z^{(1)}(k)$ may be unsuitable. In order to overcome the above-mentioned drawbacks, the improved decimal-code genetic algorithm was used to obtain the optimal coefficient α value to set proper background value $z^{(1)}(k)$.What is more, the one-point linearity arithmetical crossover was put forward, which can greatly improve the speed of crossover and mutation so that the proposed GM(1,1)-IGA can forecast the short-term daily load successfully.

The paper is organized as follows: section Ⅱ proposes the grey forecasting model GM(1,1): section Ⅲ presents Estimate α by improved genetic algorithm: section Ⅳ puts forward a short-term daily load forecasting realized by GM(1,1)-IGA and finally, a conclusion is drawn in section Ⅴ.

2. The Forecasting Model—GM(1,1)

2.1 The Forecasting Model

The forecasting model [14] has three operations: (a) accumulated generation, (b) inverse accumulated generation, and (c) grey modeling. In grey forecasting, the accumulated generating operation (AGO) and inverse accumulated generating operation (IAGO) are the main methods which provide a manageable approach to treating disorganized evidence [15].

The AGO equation is $x^{(r)}(k)=x^{(r)}(k-1)+x^{(r-1)}(k)$

The IAGO equation is $x^{(r-1)}(k)=x^{(r)}(k)-x^{(r)}(k-1)$

The original series is $x^{(0)}=(x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n))$

The r times accumulated series is $x^{(r)}=(x^{(r)}(1),x^{(r)}(2),x^{(r)}(3),\cdots,x^{(r)}(n))$.

2.2 Grey Forecasting Model GM(1,1)

The generated series can be used to build a GM, which was developed by applying the approximate exponential law. GM(1,1) is a one-variable and one-degree differential equation, which applies AGO, IAGO, and other equations to predict a series of values. Intrinsically speaking, it has the attributes of requiring less data to construct the model.

The grey model GM(1,1) constructing process was described below:

- First :To take the AGO

Denote the original data sequence by $x^{(0)}=(x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n))$, and $x^{(0)}$ is the given discrete n-th-dimensional sequence.

The 1-AGO formation is defined as: $x^{(1)}=(x^{(1)}(1),x^{(1)}(2),x^{(1)}(3),\cdots,x^{(1)}(n))$

Where $x^{(1)}(1)=x^{(0)}(1)$, and $x^{(1)}(k)=\sum_{m=1}^{k} x^{(0)}(m)$, $k = 2, 3\dots$ n.

- Second :To set the α value to fine $z^{(1)}$

According to GM(1,1), we can form the following first-order grey differential equation:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b$$

Where α was called the developing coefficient of GM, and b was called the control variable.

Denoting the differential coefficient subentry in the form of difference, we can get:

$$\frac{dx^{(1)}}{dt}=\frac{x^{(1)}(k+1)-x^{(1)}(k)}{k+1-k}=x^{(1)}(k+1)-x^{(1)}(k)$$

Before a grey GM(1,1) model was set up, a proper α value needed to be assigned for a better background value $z^{(1)}(k)$. The sequence of background values was defined as:

$$z^{(1)}=\left\{z^{(1)}(1),z^{(1)}(2),\cdots,z^{(1)}(n)\right\}$$

Among them $z^{(1)}(k)=\alpha*x^{(1)}(k)+(1-\alpha)*x^{(1)}(k-1)$, where , k=2, 3… n, $0\le\alpha\le1$

For convenience, the α value was often set to 0.5, the $z^{(1)}(k)$ was derived as:

$$z^{(1)}(k)=\left[x^{(1)}(k)+x^{(1)}(k-1)\right]/2$$

However, this constant α might not be optimal because the different questions might need different α value. And, both developing coefficient α and control variable b were determined by the $z^{(1)}(k)$. The process of the original grey information for whitening may be suppressed resulted from the coefficient α was constant. Hence, the accuracy of prediction value $\hat{x}^{(0)}(k)$ in GM(1,1) model would seriously be decreased. In order to correct the defect, the coefficient α must be a variable based on the feature of problems, so we estimate α by genetic algorithms.

- To construct accumulated matrix B and coefficient vector X_n.

Applying the Ordinary Least Square (OLS) method obtains the developing coefficient α , b was as follows:

$$B=\begin{bmatrix}-z^{(1)}(2) & 1\\ -z^{(1)}(3) & 1\\ \vdots & \vdots\\ -z^{(1)}(n) & 1\end{bmatrix}\text{ and } X_n=\left[x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n)\right]^T \text{ So } \left[\hat{a},\hat{b}\right]^T=\left(B^T*B\right)^{-1}*B^T*X_n$$

- To obtain the discrete form of first-order grey differential equation, as follows:
  The solution of $x^{(1)}$ is

$$\hat{x}^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{\hat{b}}{\hat{a}}\right)*e^{-\hat{a}k}+\frac{\hat{b}}{\hat{a}}\qquad k=0,\ 1\ldots$$

And the solution of $x^{(0)}$ is $\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)=(e^{-a}-1)*\left[x^{(0)}(1)-\frac{\hat{b}}{\hat{a}}\right]*e^{-\hat{a}k}$ k=0, 1, 2…

2.3 From The Improved GA To Estimate α

In order to estimate the accuracy of grey mode GM(1,1), the residual error test was essential. Therefore, the objective function of the proposed method in this paper was to ensure that the forecasting value errors were minimum. The objective function was defined as mean absolute percentage error (MAPE) minimization as follows:

$$\min MAPE=\sum_{k=1}^{n}\left\|e(k)\right\|\text{ , Where, } e(k)=\left\|\frac{\hat{x}^{(0)}(k)-x^{(0)}(k)}{x^{(0)}(k)}\right\|\times100\%$$

$x^{(0)}(k)$ is original data, $x^{(0)}(k)$ is forecasting value, n is the number of sequence data. However, from the above description of the establishment of GM(1,1), we can get: In GM(1,1), the value of parameter α can determine $z^{(1)}$, and, both developing coefficient a and control variable b were determined by the $z^{(1)}(k)$.What is more, the solution of $x^{(0)}$ was determined by a and b, so the key part of the whole model selecting process was the value of α .There is kind of complicated nonlinear relationship between α and residual errors, and this nonlinearity was hard to solve by resolution, so the optimal selection of α was the difficult point of GM(1,1).

GA is a random search algorithm that simulates natural selection and evolution. It is finding widespread application as a consequence of two fundamental aspects: the computational code is very simple and yet provides a powerful search mechanism. They are function independent which means they are not limited by the properties of the function such as continuity, existence of derivatives, etc. Although the binary representation was usually applied to many optimization problems, in this paper, we used the improved decimal-code representation scheme for solution. The improved decimal-code representation in the GA offers a number of advantages in numerical function optimization over binary encoding. The advantages can be briefly described as follows:

- **Step1**: Efficiency of GA is increased as there is no need to convert chromosomes to the binary type,
- **Step2**: Less memory is required as efficient floating-point internal computer representations can be used directly,
- **Step3**: There is no loss in precision by discrimination to binary or other values, and there is greater freedom to use different genetic operators [1].

We utilized the improved decimal-code representation scheme for searching optimal coefficient α value in grey GM(1,1) model. In this paper, we proposed one-point linearity arithmetical crossover and utilized it to select the value of α ; it can greatly improve the speed of crossover and mutation. The steps of the improved decimal-code representation scheme are as follows:

(1) Coding： Suppose $\alpha \in [0,1]$ is a binary string of C bits, then let every n bits transform a decimal from right to left.(n<C, the values of n and C are ensured by precision)

(2) Randomize population: Select one integer M as the size of the population, and then select M points stochastically from the set $[0,1]$, as $\alpha(i,0)(i=1,2,\cdots,M)$, these points compose the individuals of the original population, the sequence is defined as: $P(0)=\{\alpha(1,0),\alpha(2,0),\cdots,\alpha(M,0)\}$

(3) Evaluate the fitness: In the selection step, individuals $\alpha(i,k)$ are chosen to participate in the reproduction of new individuals. The individual $\alpha(i,k)$ with the highest fitness $F(\alpha(i,k))$ has the priority and advances to the next generation.

- **Step4**: Selection: In this paper, we calculate individual selected probability $p_i^{(k)} = F(\alpha(I,K)) \Big/ \sum_{i=1}^{m} F(\alpha(i,k))$ respectively according to their fitness functions $F(\alpha(i,k))$, then we adopt the roulette wheel selection scheme, so that the propagated probability of respective individual is $p(k)$, after that we take the inborn individual to compose the next generation $p(k+1)$.
- **Step5**: Crossover and Mutation: Coding and crossover are correlative; we utilized the decimal-code representation, so we propose a new crossover operator "one-point linearity arithmetical crossover".

1) Select the fit two individuals with probability of crossover p_c.

2) For the two selected individuals, we still adopt the random selection means to ensure the crossover operator.

3) Crossover:

① We exchange their right strings each other.

② The bit on the left of crossover can be calculated through the following algorithm:

Gene analysis: $Z_{ik} = \beta * Z_{ik} + (1-\beta) * Z_{ik}$, $Z_{jk} = \beta * Z_{jk} + (1-\beta) * Z_{jk}$

Exchange the back gene: $Z_{ik} = \beta * Z_{ik} + (1-\beta) * Z_{jk}$, $Z_{jk} = \beta * Z_{jk} + (1-\beta) * Z_{ik}$

The $\beta \in [0,1]$ is called crossover coefficient, it is chosen each time by random crossover operation.

4)Mutation: There is a new mutation operation: when the mutation operator was chosen, the new gene value is that a random number within the domain of weight, which is operated into a weighted sum with original gene value. If the value of mutation operator is Z_i, the mutation value is:

$$Z_i = \alpha * r + (1-\alpha) * Z_i$$

And α is the mutation coefficient, $\alpha \in [0,1]$. r is a random number, $r \in [Z_{i\min}, Z_{i\max}]$.It is selected randomly every time when mutation operation is happening. Therefore, the new offspring can be created through crossover and mutation operations.

- **Step6:** Quit principle: Select the remaining individuals in the current generation to reproduce the individuals in the next generation, then evaluate the fitness value and judge whether the algorithm fulfils the quit condition. If it is certifiable, in this case the α value is optimal solution, else repeat from Step 4 until all individuals in population meet the convergence criteria or the number of generations exceeds the maximum of 100.

3. Power Load Forecasting Example

In this section, we try to evaluate the performance of GM(1,1)-connection improved genetic algorithm.

First: The daily load data sequences of m days are defined as $\{x(k) \mid k = 1,2,\cdots,n\}$, we measured the power load each hour, and the load sequence vector is a twenty-four-dimensional data.

01 the time of day: $X_{01} = \{x_{01}(i) \mid i = 1,2,\cdots,m\}$, 02 the time of day: $X_{02} = \{x_{02}(i) \mid i = 1,2,\cdots,m\}$

j the time of day: $X_j = \{x_j(i) \mid i = 1,2,\cdots,m\}$, 24 the time of day: $X_{24} = \{x_{24}(i) \mid i = 1,2,\cdots,m\}$

Where m is the number of modeling days, X_j is the daily load data sequence of the j-th time of day.

Second: We utilize improved genetic algorithm to select the value of α for respective load data sequence X_j. After that, we can calculate a and b, then we utilize GM(1,1)-connection improved genetic algorithm to predict the load forecasting of the j-th time of the (m+1)-th day, so we could get $X_j(m+1)$, and the twenty-four forecasting values of the (m+1)-th day structure the load data sequence $\{x_j(m+1) \mid j = 1,2,\cdots,24\}$.

There was an example of GM(1,1)-connection improved genetic algorithm (GM(1,1)-IGA), both the two forecasting daily load data curves (July26) and the original daily load data curve were drawn simultaneously on Fig 1.

At Fig 1, we can get that the forecasting load data curve of GM(1,1)-IGA was more closed to the original daily load data curve than GM(1,1)'s. For further analysis, this paper selects relative errors as a criterion to evaluate the model.

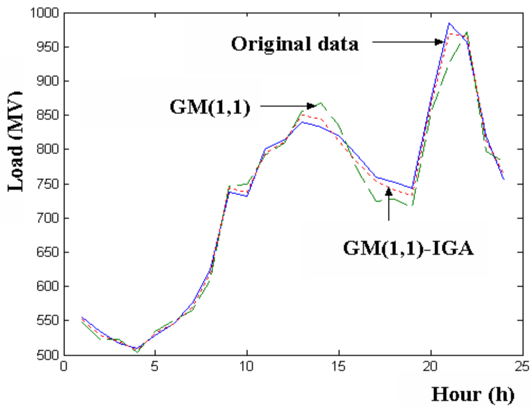

Fig 1. Original data and forecasting value

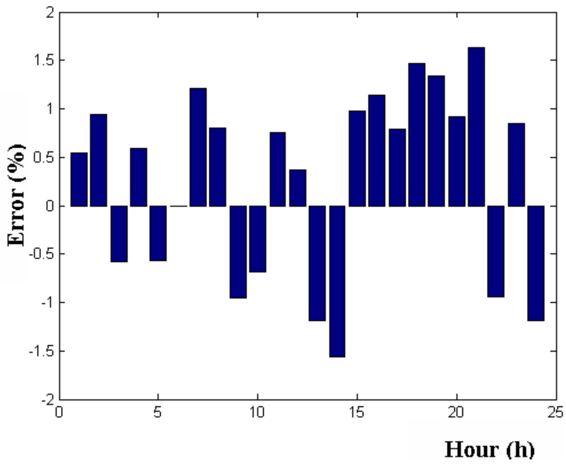

Fig 2. The errors of GM (1, 1)-IGA

4. Conclusion

The paper proposes GM(1,1)-connection improved genetic algorithm (GM(1,1)-IGA) for power short-term load forecasting. Adopting decimal-code representation scheme, the improved genetic algorithm is used to select the optimize α value of GM(1,1) model. The paper also puts forward the one-point linearity arithmetical crossover which can greatly improve the speed of crossover and mutation, so that the GM(1,1)-IGA can forecast the short-term daily load successfully. The GM(1,1)-IGA is characteristic of being simple and easy to develop, therefore, it is appropriate as an aid tool to solve the forecasting problems in power system.

5. References

[1] W. Christise, "Short-Term Load Forecasting Using General Exponential Smoothing," DEEE Tr. On Power Apparatus and systems. Vol. PAS - 90, pp. 900-910, April, 1971.

[2] J. L. Deng, "Control problems of grey systems," Systems and Control Letters, vol. 1, no. 5, pp. 288-294, 1982.

[3] P. Gupta and K. Yamada,"Adaptive Short-Term Load Forecastingof Hourly Loads Using Weather Information," IEEE Tr. On Power Apparatus and Systems. Vol Pas-91, pp2085-2094,1972.

[4] Abdolhosien S. Dehdashti, James RTudor, Michael C.Smith, "Forecasting Of Hourly Load By Pattern Recognition- A Deterministic Approach," IEEE Tr. On Power Apparatus and Systems, Vol. AS-101, No.9 Sept 1982.

[5] S. Rahrnan and R Bhamagar, "An expert System Based Algorithmfor Short-Term Load Forecast," IEEE Tr. On Power Systems , Vol. AS-101, No. 9 Sept. 1982

[6] D.W. Bunn, E.D. Farmer, "Comparative Models for Electrical Load Forecasting". John Wiley & Son, 1985, New York.

[7] Zwe-Lee Gaing, Rong-Ceng Leou. "Optimal Grey Topological Predicting Approach to Short-term Load Forecasting in Power System". IEEE Tr. Power Engineering Society Meeting, Vol 3,2002,pp:1244-1250

[8] Nima Amjady, "Short-Term Hourly Load Forecasting Using Time-Series Modeling with Peak Load Estimation Capability,"IEEE Transactions on Power System, Vol. 16, No. 3, August 2001.

[9] A.D. Papalexopoulos and T.C. Hesterberg, " A Regression-based Approach to Short-Term Load Forecasting," IEEE Trans. On Power System, Vol. 5, No. 4, pp. 1535-1547, 1990.

[10] M. T. Hagan, and S. M. Behr, "Time Series Approach to Short-Term Load Forecasting," IEEE Trans. on Power System,Vol. 2, No. 3, pp. 785-791, 1987.

[11] S 0 a e r o and M R Irving, "A Genetic Algorithm For Generator Scheduling In Power Systems," IEEE Tr.Electrical Power & Energy Systems, Vol 18. No 1,pp 19-26 1996.

[12] Xie Naiming, Liu Sifeng. "Research on Discrete Grey Model and Its Mechanism". IEEE Tr. System, Man and Cybernetics, Vol 1, 2005,pp:606-610

[13] J. Grey Syst., "Introduction to grey system theory," vol. 1, no.1,pp. 1–24, 1989

[14] Edmund, T.H. Heng Dipti Srinivasan A. C. Liew. "Short Term Load Forecasting Using Genetic Algorithm And Neural Networks".IEEE Catalogue No: 98EX137 pp 576-581

[15] Chew, J.M. , Lin, Y.H. , and Chen, J.Y., "The Grey Predictor Control in Inverted Pendulum System", Journal of China Institute of Technology and Commerce, Vol.11, pp. 17-26, 1995