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An improved grey model for power outages prediction in medium-voltage distribution system / Zhang, Y., Mazza, A., Bompard, E.F., Roggero, E., Galofaro, G.. - ELETTRONICO. - (2019). (The 8th DACH+ Conference on Energy Informatics Salzburg 26-27 September 2019).

Availability:

This version is available at: 11583/2757206 since: 2020-01-30T18:09:36Z

Publisher:

Springer

Published

DOI:

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RESEARCH

An improved grey model for power outages prediction in medium-voltage distribution system

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Abstract

The number of outages in a medium-voltage distribution system directly affects the reliability and resilience of power grid. An accurate prediction of the outages is critical for the planning, operation and maintenance of electric power system. In this paper, the grey model GM(1,1) was introduced to investigate the pattern hidden in the total number of outages in every month. Different from the traditional grey model, the parameter in GM(1,1) was optimized with the Genetic Algorithm (GA). To avoid the dramatic increase of errors due to multi-steps prediction, a rolling mechanism is also adopted in the grey model to capture the latest trend in the data. The proposed method was applied to predict the outage number in an urban distribution network. The method was verified with the accurate predictions.

Keywords: distribution system; outages; grey model; genetic algorithm; rolling mechanism

Introduction

Unlike the power transmission system, the distribution network usually faces the challenges due to the large number of equipment, complex structure and various customers, which raise the possibilities of power supply interruptions to a large extent [1]. In the meanwhile, the complicated causes and unclear relations bring difficulties to an accurate outage prediction. Since the consumers' satisfaction is deeply dependent on the number of interruptions, the Distribution System Operators (DSOs) have been seeking a reliable way to forecast the number of outages for a better maintenance plan and operations [2].

In order to deal with this problem, there are some researches trying to analyze the impact of external factors to the outage in power grid in statistical models. In theory, with the information of all the potential causes collected, it becomes possible to build a regression model to predict the number of outages under a certain condition. For example, the adverse weather conditions are usually taken as an important factor for the reliability assessment in power system [3]. However, due to the fact that most of the utilities focus more on the fast repair of electrical equipment rather than detailed investigation of failure causes, there are typically limited information to investigate the real reasons behind an outage [4]. Moreover, as the majority of feeders in an urban distribution network, the underground cables are not as sensitive as overhead lines to the external factors, which weakens the performance of traditional regression models.

The grey model, which is a classic theory for uncertain issues with limited sample size and poor data information, is a promising solution for the outage prediction

problems. As a frequently used prediction technique, GM(1,1) has been applied to various engineering problems [5, 6], including the electrical load forecasting, wind power prediction, and so on. In our study, an improved grey model was adopted to forecast the number of outages due to the absence of causes and external information. Compared to the typical basic grey model, the GA optimization was introduced to determine the proper parameter with an objective as the minimum error between predictions and real values. Furthermore, a rolling mechanism was applied to track the latest trend of data dynamically and improve the precision of estimation.

Method

Basic grey model GM(1,1)

GM(1,1) is a classic prediction model based on the grey theory, which could uncover the inherent regularity from discrete data series with limited samples. It decreases the randomness of the trend by accumulating the original data series. Given the nonnegative original data sequence $\mathbf{x}^{(0)}$ as $x^{(0)} = [x_1^{(0)}, x_2^{(0)}, \dots, x_N^{(0)}]$, where N is the length of data sequence. Then each element of the monotonic increasing data sequence $\mathbf{x}^{(0)}$ could be obtained by accumulating the first k elements of the original data: $x^{(1)} = [x_1^{(1)}, x_2^{(1)}, \dots, x_N^{(1)}]$, $x_k^{(1)} = \sum_{i=1}^k x_i^{(0)}$, $k = 1, \dots, N$.

The k -th background value z_k in the above equation is defined as the average value of the k -th and $(k-1)$ -th accumulated data as $z_k = \mu x_{k-1}^{(1)} + (1 - \mu)x_k^{(1)}$, $k = 2, \dots, N$.

Given the original data, the parameters a and u could be determined with the least square method as follows:

$$\begin{bmatrix} a \\ u \end{bmatrix} = \left(\begin{bmatrix} -z_2 & 1 \\ -z_3 & 1 \\ \dots & \dots \\ -z_N & 1 \end{bmatrix}^T \times \begin{bmatrix} -z_2 & 1 \\ -z_3 & 1 \\ \dots & \dots \\ -z_N & 1 \end{bmatrix} \right)^{-1} \times \begin{bmatrix} -z_2 & 1 \\ -z_3 & 1 \\ \dots & \dots \\ -z_N & 1 \end{bmatrix}^T \times \begin{bmatrix} x_2^{(0)} \\ x_3^{(0)} \\ \dots \\ x_N^{(0)} \end{bmatrix}$$

The estimation of the accumulated values could be obtained as below from the solution of white differential equation [7]

$$\hat{x}_{k+1}^{(1)} = \left(x_1^{(0)} - \frac{u}{a} \right) e^{-ak} + \frac{u}{a}$$

Optimization of μ by GA

In traditional grey model GM(1,1), the weight μ for calculating background values are fixed as 0.5, which means that the background values are equal to the average of two continuous accumulated data [7]. However, the value of μ is possible to be varying within the interval [0,1]. An optimization of μ could be carried out for building a better grey model. In this paper, the GA technique is used for finding the optimized value of μ and improve the flexibility of the grey model.

The GA optimization [8] originated from the theory of natural evolution and mimics the process of natural selection, including mutation, crossover and selection. It starts with a population of randomly distributed solutions in the given domain. Each candidate solution corresponding to the value of μ differs from the others. In our case, the objective of the optimization process is to minimize the errors between

the estimated values and real values. Therefore, the Mean Absolute Percentage Error (MAPE) is used as the objective function, which is defined as below:

$$MAPE(\mu) = \frac{1}{N} \sum_{k=1}^N \left| \frac{x_k^{(0)} - \hat{x}_k^{(0)}(\mu)}{x_k^{(0)}} \right|$$

Rolling Mechanism for GA-based GM(1,1)

In practical cases, the trend inside a data sequence is typically significant in a limited period. Since only the latest data reflect the development trend, the rolling mechanism with a sliding window for the building of GM(1,1) is an effective method to deal with the seasonal data.

In the rolling mechanism, the GA-based GM(1,1) is always built on the p original data points $[x_1^{(0)} \ x_2^{(0)} \ \dots \ x_p^{(0)}]$ to predict the following q data points $[x_{p+1}^{(0)} \ x_{p+2}^{(0)} \ \dots \ x_{p+q}^{(0)}]$. In this case the length of sliding window is p . Once the new information is acquired, the predicted q data points will be replaced with the real values. Then most updated p real values $[x_{q+1}^{(0)} \ x_{q+2}^{(0)} \ \dots \ x_{p+q}^{(0)}]$ will be utilized to predicted the next q values $[x_{p+q+1}^{(0)} \ x_{p+q+2}^{(0)} \ \dots \ x_{p+2q}^{(0)}]$. These steps will be iterately implemented over all the data set.

Case Study

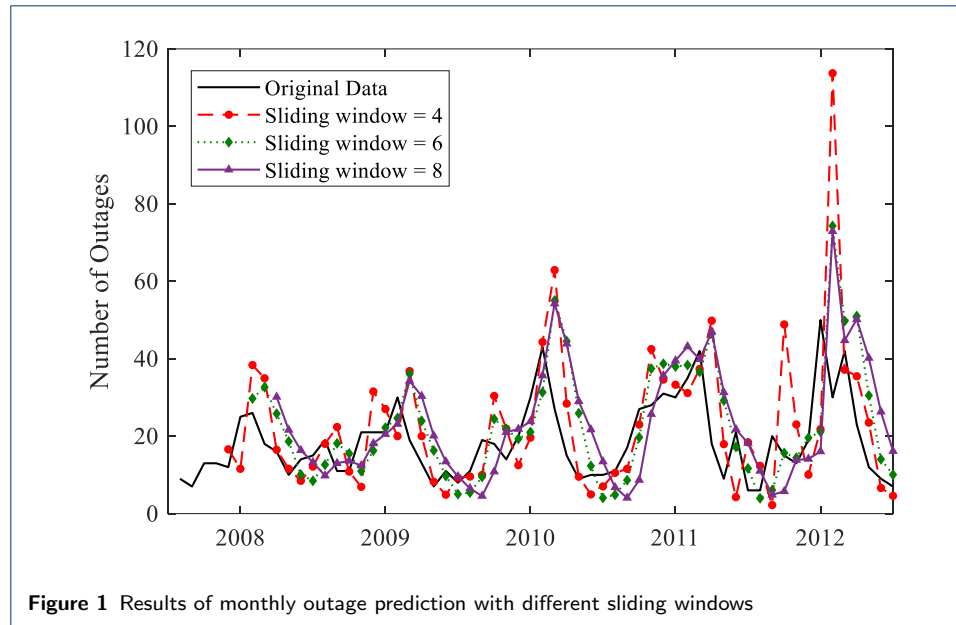
In our study, the 5 years' records of outage in the local urban distribution network have been collected and used for building the grey model. From 2008 to 2012, the number of outages in every month increased during summer and decrease in winter. The possible reason is that during summer, the higher temperature and less precipitation bring challenges to the insulation of power equipment. The aging process of electrical devices accelerates during such critical weather conditions. However, there is also a potential increasing trend in the annual total number of outages. If we focus only on the summer period, the outage number has seen a slight increase during the 5 years. It may be caused by the more frequent heat waves in summer. Meanwhile, the warmer summer encourages more families to install the air-conditioners in their houses, which significantly increase the load in power grid. Outages are prone to happen in the overload state.

Building the GA-based GM(1,1) with rolling mechanism

The monthly outage number in the urban distribution network among the five years will be predicted by employing the GA-based GM(1,1) in this section. In order to capture the latest trend of the change in outage numbers, the rolling mechanism is applied. The length of sliding window p will be tested on different values with comparison of forecasting errors. The length of prediction data q is always set as 1 in our simulation. The prediction results are shown in Figure 1.

Conclusion

In this paper, an improved grey model is proposed to forecast the number of outages in the urban distribution network. An accurate prediction of the outage number provides a useful indicator for the maintenance plan and investment in the construction



for a stronger power grid. The parameters for building the traditional grey model GM(1,1) is first improved with the optimization techniques. Since the monthly outage number is a seasonal data sequence, the rolling mechanism is introduced to improved the ability of capturing the change of trend.

Funding

Add funding information here.

Availability of data and materials

Point to sources of data and materials in this article. If there are none, state so. Do not remove this section.

Author's contributions

YZ implemented the prediction model and analyzed the results. AM and EB contributed in the novelty of the model. ER and GG participated in the design of the study. All authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

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