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Abstract—**Annual power outages in distribution network are highly related to the reliability of the power grid and directly affect the customers' satisfaction. The severe weather conditions, increasing loads as well as aging equipment are all potential threatens to the electrical grid infrastructure. A good prediction of the number of outages is essential for the maintenance planning and cost benefit analysis of investment. In order to predict the out-of-service cases in the power grid, the GM (1,1) (first-order Grey Modelling) forecasting method is introduced in this paper. To improve the accuracy of the prediction, the PSO (particle swarm optimization) algorithm is applied for the parameter optimization in the modeling. The number of outages in the next two years of a medium-voltage urban distribution network are predicted based on the records in the past 7 years. The good performance of the simulation results verifies the proposed forecasting method.**

Keywords—Distribution system, grey prediction model, outages, PSO.

X. Introduction

As the terminal of power system, the distribution network is characterized with the multi-type lines, wide area and complex structure. Due to this nature, the occurrence of interruptions has various causes. In general, there are three main factors for distribution system outages: intrinsic factors, like the defects of equipment; external factors, like the damages from animals or lightning; and human error factors [1]. However, utilities usually focus more on the repair of power system components rather than detailed investigation of failure causes. Therefore, the outage records contain only limited information for tracing back and analyzing the causes.

As one of the densest distribution networks, the Turin area suffers an increasing number of outages on the underground medium voltage grid. The forecasting of number of outages is an important reference for the DSO to anticipate the maintenance staff and evaluate the repairing cost from an operational point of view [2]. With more frequent heat waves, aging equipment and growing power demand, the outage number is increasing under multiple reasons. The grey model prediction method could capture the increasing trend of outages avoiding detailed analysis of factors affecting the performance of distribution network [3].

Outage management is critical for distribution system operators (DSO) as a long-standing problem [4]. There are various researches aiming at damage assessment of the power grid with statistical analysis [5][6]. These methods usually combine the historical power outage records with the environmental data as a forecasting model. However, in the urban distribution grid, most of the medium voltage feeders are underground cables, which brings the difficulties to analyze the relation between the external factors and the failures of underground power feeders. The ability to forecast the number of outages in a period is important for the DSO to arrange the maintenance plans and improve the grid resilience [2][7]. The annual outage prediction based on the records in a few years is also challenging due to the limited data and uncertainty.

The grey theory, which is proposed to solve the uncertain problems with rare or inadequate data [8], has seen various applications to the engineering problems [9][10]. Different from the typical forecasting models like Autoregressive Integrated Moving Average (ARIMA), the grey theory could overcome the limitation of insufficient data collections for calibrating the model parameters. Moreover, the ability to deal with sparse data enables it as a practical and user-friendly forecasting method. A grey model is utilized in [11] for predicting the failure rate of power substation in service to improve the safety and reliability of the equipment. To deal with the uncertainty of failure rate prediction in both fault stabilization period and fault loss period, a grey-linear regression model is used in [3]. The seasonal grey model, PSO-based grey model and the adaptive parameter learning mechanism based seasonal fluctuation grey model are built and compared in [9] to analyze the seasonal fluctuations of the electricity consumption of the primary economic sectors. A rolling mechanism designed on the principle of "new information priority" is combined to an optimized grey prediction model to forecast the electricity consumption in [10].

Among the forecasting models based on the grey theory, the GM(1,1) model is the most popular one with one variable and its one-order equations. The annual number of outages in urban distribution network can be predicted with the grey theory model because there is inadequate information about the factors in records for outages.

In typical grey models, the background values are defined as the average of two accumulative values. In this paper, the particle swarm optimization method will be introduced to determine the optimized weights for calculating the background value with an objective as the minimum error between simulation results and the real values. Compared with the typical models, the PSO-based grey model improves the accuracy of the prediction and achieves satisfactory performance.

In this paper, the PSO-based grey model is successfully applied to the prediction of annual number of outages. The remainder of this paper is organized as follows: Section II describes the basic theory and mathematics about GM(1,1). Section III introduces the PSO for the parameter optimization in the grey model. Section IV is dedicated to the application of PSO-based grey model to the prediction of outages based on the given records. The validity of the forecasting methods is verified with the good performance of the prediction results.

XI. Basic Grey Prediction Model

Grey model is a classic method for studying the trend from discrete data series with limited samples and inadequate information. By accumulating the original data series, the randomness between samples could be reduced and a clear trend is possible to be revealed. Therefore, the first step of grey model is to add up the values.

In grey model, the data are denoted as vector $\mathbb{X}^{(0)}$ with a superscript (0) for original dataset. The original data vector contains N data points from $\mathbb{X}^{(0)}(1)$ to $\mathbb{X}^{(0)}(N)$. The inherent properties and the trend among the original data points can be uncovered with the grey prediction model, whose procedures are as follows:

1) Create a new vector $\mathbb{X}^{(0)}$ by accumulating the first k elements of original data $\mathbb{X}^{(0)}$

$$\mathbb{X}^{(1)}(k) = \sum_{i=1}^{k} \mathbb{X}^{(0)}(i) \qquad k=1, \ldots, N \tag{1}$$

where the superscript (1) refers to the accumulated data.

2) Build the background value as $\mathbb{Z}(k)$

The k-th background value $\mathbb{Z}(k)$ is defined as the average value of the k-th and (k-1)-th accumulated data as shown in eq. (1).

$$\mathbb{Z}(k) = 0.5\mathbb{X}^{(1)}(k-1) + 0.5\mathbb{X}^{(1)}(k) \tag{2}$$

where k=2, …, N.

3) Estimate the model parameters a and b

The first-order grey differential equational of a single variable is given in eq. (3) [10]

$$\mathbb{X}^{(0)}(k) + a\mathbb{Z}(k) = b \tag{3}$$

where k=2, …, N.

The corresponding white differential equation is as follows:

$$\frac{\mathrm{d}\mathbb{X}^{(1)}(t)}{\mathrm{dt}} + a\mathbb{Z}(t) = b \tag{4}$$

Where a and b are the development coefficient of the system and endogenous control grey scale, respectively.

By rewriting the above equation in the matrix format, we could get the following

$$\begin{bmatrix} \mathbb{X}^{(0)}(2) \\ \mathbb{X}^{(0)}(3) \\ \vdots \\ \mathbb{X}^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -\mathbb{Z}(2) & 1 \\ -\mathbb{Z}(3) & 1 \\ \vdots & \vdots \\ -\mathbb{Z}(n) & 1 \end{bmatrix} \times \begin{bmatrix} a \\ b \end{bmatrix} \tag{5}$$

With the known original data $\mathbb{X}^{(0)}$ and background values $\mathbb{Z}$ available, the parameters a and b could be estimated by the least square method.

4) Derive the estimation values of the accumulated data

Once the parameters a and b of the grey prediction model are obtained, the direct output of the model is the estimation of accumulated values as in eq. (6)

$$\hat{\mathbb{X}}^{(1)}(k+1) = \left(\mathbb{X}^{(1)}(1) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a} \tag{6}$$

The vector $\hat{\mathbb{X}}^{(1)}$ is the estimation of vector $\mathbb{X}^{(1)}$ with (n-1) values.

5) The prediction of grey theory model

The estimation of the original data is determined with eq. (7)

$$\hat{\mathbb{X}}^{(0)}(k+1) = \hat{\mathbb{X}}^{(1)}(k+1) - \hat{\mathbb{X}}^{(1)}(k) \tag{7}$$

XII. PSO-based Grey Prediction Model

One of the effective measures to improve the accuracy of typical grey model is to calculate the background value $\mathbb{Z}(k)$ with optimized weights on two continuous values as in the following equation:

$$\mathbb{Z}(k) = \mu\mathbb{X}^{(1)}(k-1) + (1-\mu)\mathbb{X}^{(1)}(k) \tag{8}$$

where μ is 0.5 in the typical GM(1,1) indicating an averaged number of the two cumulative values $\mathbb{X}^{(1)}(k)$ and $\mathbb{X}^{(1)}(k-1)$. However, with an optimized weight μ, the proposed model is possible to capture more details of the trend hidden in the original data. Since it is difficult to specify a clear formula for calculating the value of μ, finding the optimal value of the weight could not be accomplished by the traditional optimization methods. Instead, the heuristic optimization algorithms, like the PSO algorithm, will yield a pretty good result.

3.1 PSO Algorithm

The PSO algorithm is initialized with a group of random solutions and seeks for the optima in the given domain. In the algorithm, each solution to the optimization problem is regarded as a bird, or a "particle" in a more general way. The procedures of PSO algorithm is inspired from the stimulation of the foraging behavior of birds. Therefore, with the number of dimensions as D, there are two vectors to indicate the position X_i and velocity V_i of the i-th bird, respectively:

$$X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$$
$$V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$$

In order to find the optimal solution, each "particle" is evaluated in the objective function with a fitness value given their positions. Then, the velocity of each particle is to be adjusted according to its own and the others' searching experience. By substituting the position of the i-th particle into the objective function, the fitness of this particle at the current iteration is calculated. If the optimization problem is to find the minimal solution for the objective function, the position corresponding to the minimum fitness value among all the k iterations of the i-th particle is regarded as the personal best solution $pbest_i^k$. Similarly, the position corroding to the minimum fitness value of all the particles among the k iterations is denoted as $gbest^k$ for the global optimal solution. For a D-dimensional optimization problem, both $pbest_i^k$ and $gbest^k$ are vectors containing D elements.

The position of each particle cannot be directly changed in the PSO algorithm. Instead, it is adjusted with the velocity for the next iteration, whose value is updated with the following equation:

$$v_{id}^k = wv_{id}^{k-1} + c_1r_1\left(pbest_{id} - x_{id}^{k-1}\right) + c_2r_2\left(gbest_d - x_{id}^{k-1}\right) \tag{9}$$

where d indicate the d-th dimension of the velocity (d=1, 2, …, D), w is the inertia factor; c_1 and c_2 are the personal and group learning factor, respectively; r_1 and r_2 are the random numbers in the range [0,1].

Then, the d-th dimension of the position of the particle i is updated with the following formula:

$$x_{id}^{k} = x_{id}^{k-1} + \alpha v_{id}^{k} \tag{10}$$

where α represents the weight for the velocity.

The terminal condition of the program is usually set as the maximum number of iterations K or minimum criteria of the errors.

3.2 PSO-based GM(1,1)

In the grey model GM(1,1), the weight μ for calculating the background values $\mathbb{Z}$ could be optimized with the PSO algorithm. The objective of the optimization is to minimize the errors between the predictions and real values. In this research, the Mean Absolute Percentage Error (MAPE) is used to evaluate the performance of the grey prediction model, which is defined as below:

$$\text{MAPE} = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\mathbb{X}^{(0)}(k)-\hat{\mathbb{X}}^{(0)}(k)}{\mathbb{X}^{(0)}(k)}\right| \tag{11}$$

The procedures for the PSO-based grey model prediction are summarized in Fig. 1.

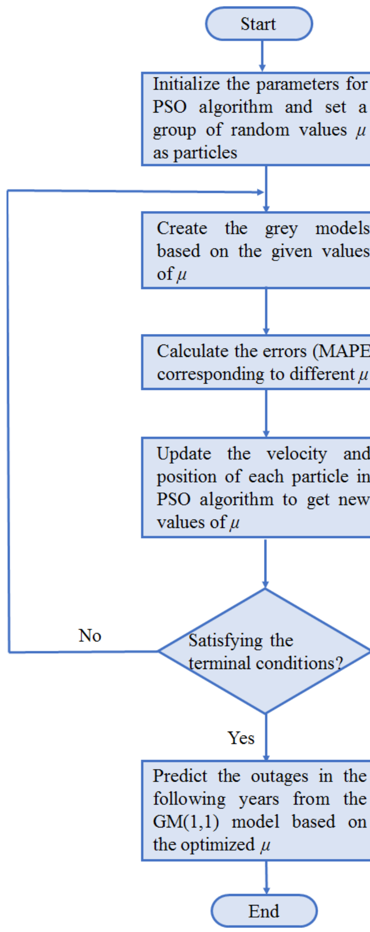

Fig. 1 PSO-based Grey Model Prediction

XIII. CASE STUDY

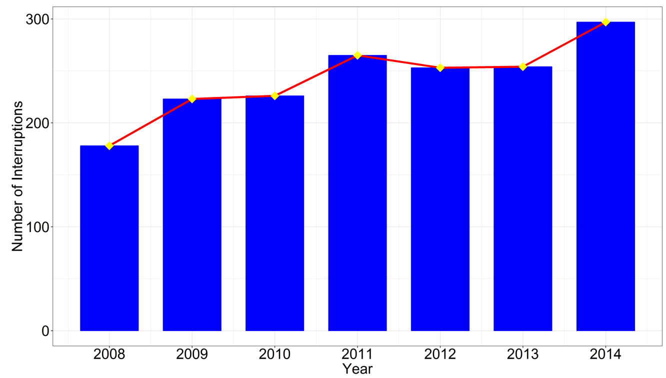

Fig. 2 Number of outage records in 7 years

In this section, the proposed PSO-based GM(1,1) is to be applied in a real-world problem: the prediction of annual outage number in an urban distribution network. In practice, the distribution network is planned in accordance with the development of the city. The capacities of the substations and feeders are usually updated with the changes of the layout of residential and industrial areas. Meanwhile, the aging process of power equipment also bring difficulties to the outage analysis in a long-time framework. Therefore, the outage number recorded within 10 years is taken as a proper time span for our research.

According to the local utility IRETI, the outage records of the urban distribution system in Turin (Italy) from 2008 to 2014 is shown in Fig. 2. In this figure, the outage number of distribution network from 2008 to 2014 is shown as blue bars. The red curve connecting the top of each bar indicates the trend of outage numbers among the 7 years. As can be seen from this figure, in spite of some fluctuations, there is an increasing trend of the outages. In this work, a grey prediction model is built with these 7-year records according to the procedures in Fig. 1.

In the first step of PSO-based GM(1,1), the parameters in the PSO algorithm are supposed to be initialized. In this work, the population of particles is set as 20 and the maximum number of iterations are both set as 50, which means that if the algorithm cannot get converged in 20 iterations, it would be automatically terminated. The value of personal learning factor c_1 is set as 0.25. In order to emphasize the group's impact and avoid the local optima, the group learning factor c_2 is set as twice the value of c_1. The maximum velocity is set as 0.1, which is 10% of the total range of μ.

Then, 20 random values distributed in [0,1] are fed to the PSO algorithm as the initial values of μ. For each iteration, the errors between the output of GM(1,1) and the real outage numbers are calculated, based on which both the personal best position of every particle and the group's best position could be determined. This information indicates the value and direction for the modification of next step's velocity. A new group of μ would be generated based on the particles' current position and new value of velocity. In our case, the PSO algorithm is converged within 20 iterations as shown in Fig. 3.

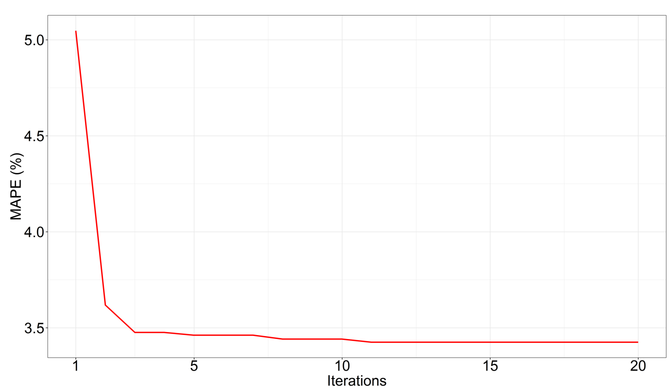

Fig. 3 Value of MPAE with increasing number of iterations

In the figure above, the MAPE between the prediction results from PSO-based grey model and the real values are demonstrated in each iteration. As a univariate optimization problem, the optimization process becomes converged very soon after a few iterations. The stable value of MAPE is 3.42%, implying a pretty good performance of the method. By applying the optimized μ into the grey model GM(1,1), the number of outages in in 2015 and 2016 can be predicted with the model derived above and compared with the results from GM(1,1) when μ=0.5, as listed in Table 1.

Table 1 Prediction results from the grey model

		Optimized μ		μ=0.5	
Year	Real Number	Prediction	Error	Prediction	Error
2015	296	301.6	1.89%	301.4	1.82%
2016	322	317.2	1.49%	315.7	1.95%

All the real outage numbers and the predicted values with PSO-based GM(1,1) from 2008 to 2016 are shown in Fig. 4. One point needs to be emphasized is that, the parameter μ is optimized based on the previous years' records, which means if the outages in the next year changes dramatically, the optimized parameter may lead to a prediction a little far from the classic model (μ is always set as 0.5). This concept is also shown in Fig. 4, where the performance of optimized grey model is better than the non-optimized grey model in most cases, while it may behave a little worse in some other cases.

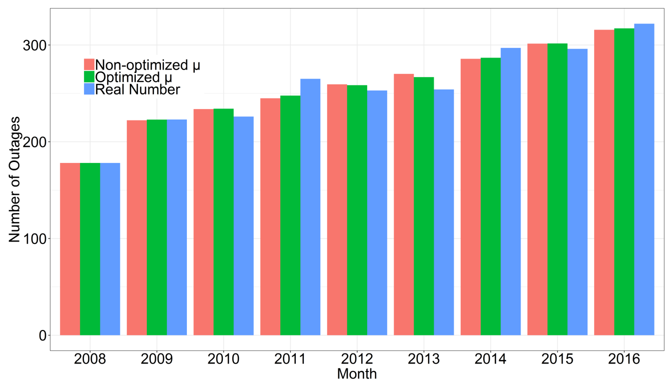

Fig. 4 The number of outages from 2008 to 2016

XIV. CONCLUSION

In this paper, an improved grey model is used to forecast the number of outages per year in the urban distribution network. As the terminal of the power grid, the reliability of distribution network directly affects consumer's satisfaction. An accurate forecasting method for the annual outages is an important referent for the planning and investment of power grid.

As a powerful heuristic optimization method, the PSO algorithm is applied in the grey model to determine the optimized parameter. With the objective function as the minimum errors between the model and real values, the first 7 years' records are used to build the PSO-based grey model. Theoretically, an optimized μ could decrease the error arisen during the first 7 years in a more accurate model. But it cannot guarantee a higher accuracy of the prediction results if the trend behind the annual records change dramatically. Fortunately, the following two years in our case study still follows the same trend as the first 7 years. In the future work, the potential impetus for the increasing of outages during the years needs to be analyzed.

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