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# A Residual Voltage Data-Driven Prediction Method for Voltage Sag Based on Data Fusion

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**Abstract:** Voltage sag is the most serious power quality problem in the three-phase symmetrical power system. The influence of multiple factors on the voltage sag level and low computational efficiency also pose challenges to the prediction of residual voltage amplitude of voltage sag. This paper proposes a voltage sag amplitude prediction method based on data fusion. First, the multi-dimensional factors that influence voltage sag residual voltage are analyzed. Second, these factors are used as input, and a model for predicting voltage sag residual voltage based on data fusion is constructed. Last, the model is trained and debugged to enable it to predict the voltage sag residual voltage. The accuracy and feasibility of the method are verified by using the actual power grid data from East China.

**Keywords:** voltage sag; residual voltage prediction; data fusion



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## 1. Introduction

Voltage sag is an inevitable short-term disturbance phenomenon that appears during power system operation, and it has become the most serious power quality problem. Voltage sag affects voltage quality and causes considerable economic losses [1,2]. The influencing degree of voltage sag mainly depends on the residual voltage amplitude. Accurate prediction of the residual voltage of the voltage sag can help in clearly understanding the impact of voltage dip on equipment and users. Furthermore, it can provide the basis for users to prevent or control voltage sag, which is very important for reducing the impact of voltage sag [3].

In refs. [4,5], the authors used the Monte Carlo method to express the uncertainty of fault occurrence, including fault type, fault location, etc., and subsequently predicted the probability distribution of voltage sag residual voltage amplitude. The Monte Carlo method cannot consider the influence of the actual environment on the prediction. The authors in [6] pointed out that the influences of generator scheduling and time-varying failure rate on the random prediction of voltage sag should be considered during the voltage sag prediction process. In ref. [7], the authors proposed an online algorithm for residual voltage amplitude prediction based on the harmonic footprint and constructed a general prediction function suitable for all voltage disturbances.

A few methods use monitoring data to predict the voltage sag index. In ref. [8], the authors used the monitoring data to analyze and discuss the randomness of voltage sag. Furthermore, the authors described the voltage sag as a random process and predicted a sag event. In ref. [9], the authors used measured data to predict the voltage sag frequency index of non-monitoring points. The authors in [10] used homologous aggregation and

fuzzy *c*-means theory to reduce the redundancy of the measured data and predict the residual voltage. The aforementioned prediction methods based on monitoring data need long monitoring times and low amounts of monitoring data, which lead to poor prediction accuracies.

This paper proposes a data-driven method for voltage sag residual voltage prediction based on data fusion. The original contributions of this study are summarized as follows:

- (1) This paper comprehensively considers the factors influencing the grid and user sides in order to predict voltage sag residual voltage. The corresponding input parameters are selected from different kinds of data and the factors that influence the residual voltage are considered more comprehensively than the Monte Carlo-based method.
- (2) This paper builds a prediction method based on data fusion to predict the residual voltage. The amount of data is increased through data fusion, and the problems of low prediction accuracy and low amount of available monitoring data are improved.
- (3) This paper presents a residual voltage prediction method for voltage sag based on data fusion, which can be integrated into power-quality-monitoring systems and used for the prevention, evaluation, and treatment of voltage sag. This method can provide users with residual voltage information and help them avoid voltage sag and formulate reasonable voltage sag prevention or treatment measures. The accuracy and efficiency of the method are verified using actual data, which gives it a strong engineering application value.

The remainder of this paper is organized as follows. The data sources of voltage sag residual voltage are described in Section 1. The residual voltage prediction method based on the improved gradient descent method is presented in Section 2. Case studies and analyses based on real power system data are shown in Section 3. The paper is concluded in Section 4.

## 2. Factors and Data Sources of Voltage Sag Residual Voltage

### 2.1. Influencing Factors of Voltage Sag Residual Voltage

Motor startup and other factors can cause voltage sag; however, these types of voltage sag are often not serious and existing measures can effectively eliminate their impact [11]. The main cause of voltage sag is a power grid fault [12]. Therefore, this paper mainly considers the impact of power grid faults during the voltage sag residual voltage prediction process.

After a grid fault occurs, the residual voltages at different nodes have varying amplitudes under different grid operation modes, and the impacts on different nodes are also different. Therefore, the influence of grid operation mode should also be considered in the prediction of the residual voltage of voltage sag. In addition, voltage sags are closely related to users. Different users are affected differently depending on the types of sags transmitted to them. Therefore, the influence of the user side should be considered in the prediction of voltage sag residual voltage amplitude. In summary, voltage sag residual voltage is related to fault conditions, grid operation mode, and the influence of the user side. The above factors are considered as the factors influencing the voltage sag residual voltage and used for selecting relevant data for voltage sag residual voltage prediction.

### 2.2. Data Sources

Voltage sag data can be obtained by the Monte Carlo random fault simulation method as follows: First, the fault parameters, such as fault type, fault distance, fault line, etc., are used as random variables and the simulation calculation is carried out by the Monte Carlo method. Second, the sag level of each bus in the area is obtained. Last, the simulated data are obtained. The simulated data can reflect the influence of system operation mode and fault on residual voltage, but cannot directly reflect the influence of external factors such as weather.

When a voltage sag occurs in the power grid, the power quality monitoring system, energy management system, user power consumption information collection system, and

other systems collect a large number of records. There are many kinds of data related to voltage sag, and the relationship between them is complicated. In this paper, the relevant factors affecting the voltage sag residual voltage are obtained from the above multi-source system. The monitoring data not only reflect the influence of system operation mode and power grid faults, but also reflect the influence of external environmental factors and user-side influence. However, the data require long-term monitoring and consist of a small number of samples.

In summary, for the voltage sag residual voltage prediction, the data attributes reflecting the factors that influence the voltage sag residual voltage are selected from the simulated and measured data. These factors are shown in Table A1 of Appendix A.

### 3. Voltage Sag Residual Voltage Prediction Method

#### 3.1. Multiple Regression Model and Gradient Descent Method

Voltage sag residual voltage is affected by many factors. Therefore, this paper uses the multiple regression model to characterize the effects of various factors on voltage sag residual voltage. This model can be expressed as follows:

$$y = f(x_1, x_2, x_3 \dots, \theta_1, \theta_2, \theta_3 \dots) \quad (1)$$

where  $y$  is the dependent variable,  $x_1, x_2, x_3 \dots$  denote the independent variables, and  $\theta_1, \theta_2, \theta_3 \dots$  represent the regression coefficients corresponding to  $x_1, x_2, x_3 \dots$ , respectively.

The gradient descent method is a type of line search framework algorithm with negative gradient as the search direction [13]. In order to minimize the loss function, the optimization model parameters are obtained iteratively until convergence is attained, and the best-matching target task is obtained.

The basic calculation process is as follows: Solving the model parameters for the loss function  $H(x_1, x_2 \dots)$  can transform it into an optimization problem of  $\min H(x_1, x_2 \dots)$ . The calculation of the gradient  $g(x_1, x_2 \dots)$  is shown in (2). It is straightforward to conclude that the negative gradient direction  $-\nabla H$  is the fastest direction of decrease of the loss function. The iterative format of the gradient descent method is given by (3). Equations (2) and (3) shown below are iteratively used to reduce the loss function and approach the minimum point, and the parameters of the optimization model can be obtained after convergence.

$$g(x_1, x_2, x_3 \dots) = \nabla H \quad (2)$$

$$x_{k+1} = x_k - s_k g_k \quad (3)$$

In (3),  $k$  is the number of iterations,  $s_k$  is the  $k$ th iteration step size, and  $g_k$  is the  $k$ th iteration gradient size.

#### 3.2. Multiple Regression Model Based on Improved Gradient Descent Method

##### 3.2.1. Model Parameters

In order to realize the voltage sag residual voltage prediction using data fusion, this paper constructs a multiple regression model based on the improved gradient descent method. This improvement requires the construction of multiple regression models for the two types of data. The simulated data model is represented by  $D_s = f(x)$ , and the input parameter is the attribute name corresponding to the simulated data in Table A1, including the common part of the two types of data. The model of the measured data is represented by  $D_m = g(y)$ , and the input parameter is the attribute name corresponding to the measured data in Table A1, including the common part of the two types of data. The output results of  $D_s$  and  $D_m$  are the residual voltage amplitudes, expressed by  $V_s$  and  $V_m$ , respectively.

As the duration of sag mainly depends on the setting value of the protection device [10], it is not predicted in this paper. It can be observed from Table A1 that there is a common input data attribute with a consistent description in the simulated and measured data. This part is represented by the set  $A_{shared}$  in this paper, and the corresponding regression

coefficient is represented by  $\theta_{shared}$ . The non-common part attributes of the two types of data are represented by  $A_s$  and  $A_m$ , and the corresponding regression coefficients are represented by  $\theta_s$  and  $\theta_m$ , respectively. The subscripts  $s$  and  $m$  represent the simulated and measured data models, respectively. During the process of searching for the optimal model parameters using the improved gradient descent method, the loss functions  $H_s(x)$  and  $H_m(z)$  of the two models are given as

$$H_s(x) = \frac{1}{2n} \sum_{i=1}^n (f(x_i) - V_s(i))^2 \quad (4)$$

$$H_m(z) = \frac{1}{2h} \sum_{j=1}^h (g(z_j) - V_m(j))^2 \quad (5)$$

where  $n$  and  $h$  are the simulated and measured data sample capacities, respectively;  $x_i$  and  $V_s(i)$  correspond to the input and output of the  $i$ th simulation data sample, respectively; and  $z_j$  and  $V_m(j)$  correspond to the input and output of the  $j$ th measured data sample, respectively.

### 3.2.2. Model Update Strategy

This paper presents an improved gradient descent method. When the output of the two models is the residual voltage amplitude, the functions of  $A_{shared}$  in both  $D_s$  and  $D_m$  are identical. Therefore, considering the simulated and measured data as the source and target domains, respectively, the prior knowledge obtained by simulation in  $D_s$  is migrated to  $D_m$  for updating  $\theta_{shared}$ . After completing the migration, the updated  $\theta_{shared}$  is substituted back into the original model and the updated  $\theta_s$  and  $\theta_m$  are recalculated to complete the single-learning process. At this time,  $D_m$  not only reflects the role of the factors influencing the voltage sag residual voltage from the information point of view, but also reveals the impacts of relevant factors on the voltage sag residual voltage from the physical point of view. The model realizes physical-information integration through knowledge migration and improves its information space and learning performance.

The traditional gradient descent method uses a constant,  $s_k$ , whose value is obtained through trial and error. This method has the following problems: (1) The learning degree of the model is different in different stages of training; and (2) It takes a certain amount of time to obtain the ideal value of  $s_k$  by multiple attempts.

In view of the above problems, this paper considers improving the step update strategy of the model. The Armijo–Goldstein criterion is introduced into the step size update process. There are two formulas for the Armijo–Goldstein criterion, which can be expressed by (6) and (7). The value of  $s_k$  satisfying (6) and (7) is called an acceptable step size factor. After the introduction of the Armijo–Goldstein criterion,  $s_k$  can be automatically updated to an acceptable step size factor and the algorithm will have superlinear convergence.

$$f(x_k + s_k d_k) \leq f(x_k) + s_k \rho g_k^T d_k \quad (6)$$

$$f(x_k + s_k d_k) \geq f(x_k) + s_k (1 - \rho) g_k^T d_k \quad (7)$$

In (6) and (7),  $f(x)$  is the objective function,  $d_k$  is the search direction,  $g_k$  is the gradient size, and  $\rho \in (0, 0.5)$  to ensure the superlinear convergence of the algorithm.

### 3.3. Overall Process

To summarize, the process of voltage sag residual voltage prediction based on data fusion is as follows:

- (1) Acquire the measured data that can reflect the factors influencing the residual voltage from the multi-source system. The simulated data are obtained by a random sag simulation calculation based on the Monte Carlo method.
- (2) Carry out data preprocessing on the simulated and measured data to adapt them to the model, and use the above data as the model input.

- (3) Build a multiple regression model based on the improved gradient descent method. During the iterative process of the gradient descent method, the model updates the model parameters and adaptively adjusts the step size based on knowledge transfer and the Armijo–Goldstein criterion until convergence is reached.
- (4) After the training is completed, the model learns the knowledge from the physical and information aspects and can predict the residual voltage amplitude.

Figure 1 shows the overall flow chart of the voltage sag residual voltage prediction method proposed in this paper.

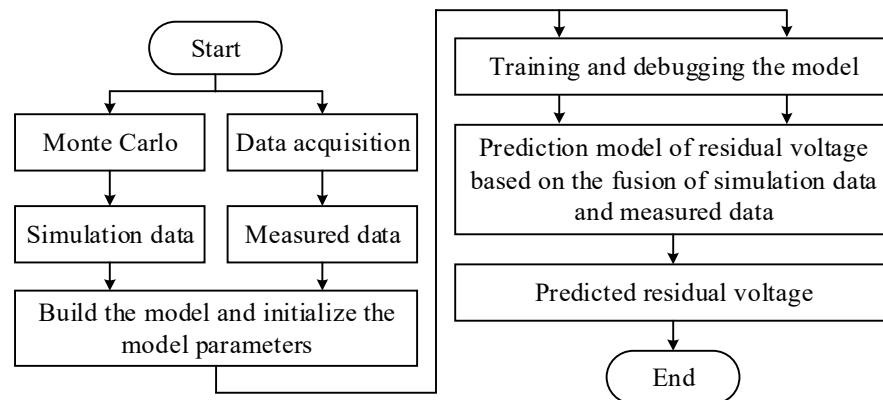


Figure 1. Flow chart of voltage sag residual voltage prediction.

## 4. Case Study

### 4.1. Data Source and Input

This paper selects 57 voltage sag measured data samples from January 2021 to December 2021 in a city in eastern China. The simulated data are obtained using Monte Carlo random simulations. The simulation calculation process is mainly realized by Bonneville Power Administration (BPA) [14], which is power system simulation software commonly used by power companies. The region selected for study has long been affected by voltage sags, and there are many industrial users that have a large proportion of sensitive equipment in the region, which is representative for this study.

### 4.2. Residual Voltage Prediction

#### 4.2.1. Prediction Results

The simulated and measured data are obtained according to Table 1 and are subsequently preprocessed. In the measured data, 44 samples are randomly selected as the training set, and the remaining 13 samples are used as the test set. The simulation dataset for knowledge transfer consists of 5280 data points obtained from the BPA-based Monte Carlo random simulation calculation.

The model uses root-mean-square error (RMSE) and mean absolute error (MAE) as the evaluation metrics. A total of 44 measured training data points and 5280 simulated training data points are input into the model for training. After training, the RMSE of the model on the training set is 0.1678, the MAE is 0.1377, and the model is able to predict the residual voltage amplitude.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - x'_i)^2} \quad (8)$$

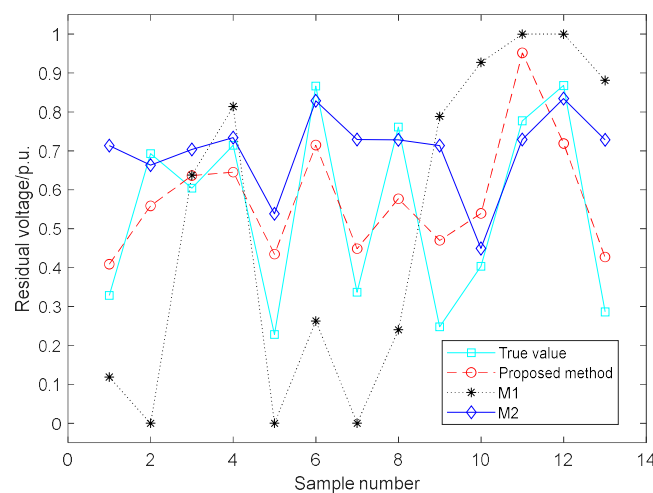
$$MAE = \frac{1}{n} \sum_{i=1}^n |x_i - x'_i| \quad (9)$$

In (8) and (9),  $i$  is the number of samples,  $x_i$  is the actual value, and  $x'_i$  is the predicted value.

**Table 1.** Evaluation metric for each method on the test set.

	Proposed Method	M1	M2
RMSE	0.1475	0.4228	0.2526
MAE	0.1379	0.3646	0.1801

After the training, the method is tested on the test set data to verify its generalization ability. In order to evaluate the model performance, it is compared with the following methods: 1. The traditional gradient descent method [13], denoted as M1 here; and 2. A support vector machine [15] (SVM, rbf-kernel,  $\epsilon = 0.0198$ ), denoted as M2 here. Figure 2 shows the prediction results of each method, Table 1 shows the evaluation indices of each method and Table 2 shows the relative error between the predicted and actual values of each method.

**Figure 2.** Test set prediction results.**Table 2.** Relative error between the predicted and real values of each method.

Sample	Method	Proposed Method (%)	M1 (%)	M2 (%)
1		24.43	−63.86	117.10
2		−19.35	−100.00	−4.25
3		5.34	5.53	16.42
4		−9.67	13.90	2.72
5		90.67	−100.00	136.10
6		−17.48	−69.65	−4.33
7		33.31	−100.00	116.63
8		−24.24	−68.46	−4.31
9		89.75	218.50	188.14
10		33.82	130.08	11.42
11		22.46	28.67	−6.15
12		−17.15	15.24	−3.86
13		49.25	207.83	154.51

The above results show that the RMSE and MAE of the proposed method are better than those of the other two methods. In addition, it can be observed from Table 2 that the relative prediction error of the method proposed in this paper is smaller than those of the other two methods. The method M1 has a large overall error and a large deviation from the error. At the same time, many output results of the method exceed the upper and lower limits of voltage amplitude and are limited by the threshold, indicating its poor convergence. Compared with M1, the output results obtained by the proposed method

do not exceed the voltage amplitude limit. The convergence is improved and the error is considerably reduced.

The model structure of M2 is more complex than that of the proposed method. However, its evaluation metric is still slightly inferior compared to that of the proposed method. Although the complex model structure adopted in M2 can improve the error to a certain extent, the problem of small sample space still significantly impacts the model performance. The method proposed in this paper uses data fusion to improve the updating strategy of the model in M1 and enhance the data mining performance. Therefore, the proposed method achieves better results compared to M2.

#### 4.2.2. Number of Iterations

Under the same convergence conditions, the numbers of iterations between the proposed method and M1 are compared in Table 3. The number of iterations of M2 is not compared here because of the different training methods.

**Table 3.** Duration and the number of iterations of single training.

Method	Iterations
Proposed method	16,101
M1	310,780

Compared with M1, the number of iterations of the proposed method is significantly reduced. This is because the proposed method modifies the update mode of the model parameters and step size through data fusion. This modification improves the learning performance of the training process and accelerates the learning process. Thus, the number of iterations is significantly reduced.

In summary, the accuracy of this method is better than that of the other two methods, and the convergence performance is also significantly improved compared with M1. Therefore, in the actual power system, this method can predict the residual voltage of the possible voltage sag at fixed intervals by collecting relevant data. This prediction can help users to prevent and control the voltage sag and reduce economic losses.

## 5. Conclusions

In this paper, a voltage sag residual voltage data-driven prediction method based on data fusion was proposed and verified. The following conclusions were obtained:

- (1) This method analyzed the relevant factors affecting the residual voltage of voltage sag from multiple dimensions. The relevant influencing factors were selected as input in order to consider the factors influencing the residual voltage of voltage sag more comprehensively.
- (2) This method considered different data characteristics and realized the prediction of voltage sag residual voltage through data fusion. Consequently, the prediction accuracy and convergence rate were improved.
- (3) The method was convenient and practical, which was verified by examples. In the future, it can be used to predict the residual voltage of voltage sag and assist the analysis of voltage sag level and consequences.

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### Abbreviations

BPA	Bonneville Power Administration
RMSE	Root-mean-square error
MAE	Mean absolute error
SVM	Support vector machine

### Nomenclature

The subscript ‘ $s$ ’ represents the simulation data model and the subscript ‘ $m$ ’ represents the measured data model.

$D_s$	Simulated data model
$D_m$	Measured data model
$A_s$	Unique parameters of simulated data model
$A_m$	Unique parameters of measured data model
$A_{shared}$	Common parameters of simulated and measured data model
$\theta_s$	Unique regression coefficient of simulated data model
$\theta_m$	Unique regression coefficient of measured data model
$\theta_{shared}$	Common regression coefficient of simulated and measured data model
$H_s(x)$	Loss function of simulated data model
$H_m(z)$	Loss function of measured data model
$g_k$	Gradient of the $k$ th iteration
$s_k$	Step size of the $k$ th iteration

### Appendix A

**Table A1.** Influencing factors of voltage sag residual voltage.

Data Sources	Attribute Name
Simulated data	Total load
	Fault impedance
Measured data	Weather
	Season
	Time
	Power user type
	Proportion of sensitive load
Common part of simulated and measured data	Line status
	Fault cause
	Monitoring bus
	Monitoring bus voltage level
	Duration of voltage sag
	Fault type
	Fault phase
Fault location	
Distance-to-fault	
	Residual Voltage



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