An Estimation and Correction Combined Method for HVDC Model Parameters Identification

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ABSTRACT Identifying correct model parameters is important for actual power system operation and control. Though existing gradient decent method shows good timeliness, it would converge to wrong results because of inevitable linearization process when applied for strongly nonlinear models. To make up this shortcoming, an estimation and correction combined method is proposed in this paper, by which the gradient method is expected to have better initial values for avoiding the local optimum trap. In the estimation process, pattern matching is utilized based on the constructed post-disturbance trajectory based typical parameters matching database. To construct the typical parameters matching database, correlation coefficient based forward and backward cluster method is applied, with which the typical parameters matching database can be updated conveniently and quickly. In the correction process, a novel comprehensive evaluation index is put forward for gradient decent method to evaluate parameter identification effects reasonably. Finally, the proposed combined parameter identification method is verified with standard high voltage direct current (HVDC) models together with parameter sensitivity analysis, and results show effectiveness.

INDEX TERMS Pattern matching, gradient decent, parameter identification, high voltage direct current.

I. INTRODUCTION

In modern power systems, effects of simulation models for theoretical research and actual operation are more and more emphasized [1], [2]. To guarantee model effectiveness, model form and its parameters should fit with actual application scenarios. In this paper, parameter identification for power system models with strong non-linearity is mainly concerned. As a popular inter-disciplinary research area, parameter identification has been researched for many industrial applications, e.g., battery model parameter estimation, motion state parameter estimation and so on [3]–[6]. The parameters identification methods are usually classified into three types including direct methods, indirect methods and artificial intelligence methods.

Direct methods enable to quantificationally describe the relationship between measurements and model parameters by transforming model analytic formula, calculating parameters gradients, linearizing system and measurement matrix [7]–[12]. In [7] and [8], least square methods are utilized for

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load and generator model parameters identification respectively. In [9], gradient decent method is applied for motor model parameters identification but the result is not always guaranteed to be optimal. In [10], Kalman filter method is adopted for linear model parameters identification. Further, Kalman filter is extended for non-linear model parameters identification by local linearization technique [11], [12]. However, the extended Kalman filter would lose effect when strongly nonlinear model is encountered.

Indirect methods also take effects for parameters identification, mainly including genetic algorithm (GA), particle swarm optimization (PSO) and so on [13], [14]. In [13], multi-stage GA is combined with sensitivity analysis for differentiated synchronous generator model parameters identification. This kind of methods rely on iterative model simulations to correct model parameters, which inevitably cause large computation burden.

Besides direct and indirect methods, artificial intelligence methods get attention recently in this research area [15]–[18]. In [15], artificial neural network (ANN) is used for generator model parameters identification. In [17], deep reinforcement learning (DRL) methods are referred for load model

parameters identification. In [18], DRL is further combined with sensitivity analysis method to solve the difficulty in high-dimension parameters identification problems. Though artificial intelligence methods compute fast, their performances are strongly related with quantity and quality of collected samples. Nevertheless, sample collection is usually tough and time-consuming for parameters identification problems.

In actual power system operation, simulation performances of high voltage direct current (HVDC) model have an important influence on accuracy of transient stability analysis (TSA) results. Considering the requirement of online TSA in computing time, parameter identification for HVDC model should be finished in a short time. Though artificial intelligence method computes fast, they require huge offline training time and could lose effect when operation scenario changes largely. Gradient decent method, as the direct method, has fast computation speed. However, its performance would be affected by the initial value and performance evaluation index considering strong nonlinearity of HVDC model. Hence, an estimation and correction combined method is put forward for parameter identification of HVDC model, where gradient decent method is used for correction. Contributions of this paper lie in three aspects.

- An estimation and correction combined method for HVDC model online parameter identification is proposed, where pattern matching method is utilized to provide initial values for gradient decent method.
- Correlation coefficient index is referred for post-disturbance trajectory based typical parameters matching database construction.
- A normalized comprehensive evaluation index is also put forward to reasonably evaluate parameter identification effects of gradient decent method.

Remaining of this paper is organized as follows: In section 2, pattern matching based model parameters estimation method is put forward together with typical parameters matching database construction method. Further, gradient decent method and the implementation of combined method are discussed in section 3. In section 4, components of HVDC model and sensitivity analysis for critical parameters selection are presented. Case studies and conclusion are presented in section 5 and 6 respectively.

II. TYPICAL PARAMETERS MATCHING DATABASE CONSTRUCTION FOR PARAMETER ESTIMATION

In this paper, parameter identification is realized by estimation and correction process. In the estimation process, online collected measurements are transformed to be post-disturbance features. With these post-disturbance features, estimated initial parameter values can be obtained by pattern matching in the typical parameters matching database. In the correction process, estimated initial parameter values are used as inputs. Then the gradient decent method is applied to adjust parameters by comparing collected actual data and

results of simulation model. The corrected parameters are finally taken as outputs. Overall scheme is illustrated in Fig.1.
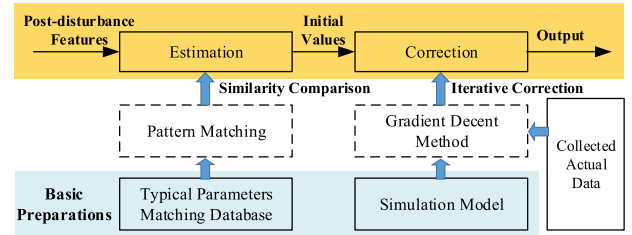

FIGURE 1. Overview of the proposed combined parameter identification method.

In this section, construction of typical parameters matching database for pattern matching is presented. Correlation coefficient based forward and backward method is demonstrated for post-disturbance trajectories categorization. On this basis, the construction and update process of typical parameters matching database is elaborated.

A. FORWARD AND BACKWARD CLUSTER METHOD

In actual applications, it is usually expected that there could be abundant typical trajectories in pattern database. Because the more the trajectories are stored in the database, the more accurate the parameter estimation result would be. However, overmuch trajectories in pattern database will increase data storage and processing burden. Hence, it is necessary to cluster the collected trajectories for better typical trajectory pattern recognition performance.

Common cluster algorithm, e.g., cluster analysis and K-means algorithm, takes Euclidean distance or Mahalanobis distance into account to evaluate the similarity among different trajectories [19]. Take Euclidean distance for example, for N collected trajectories $\{S_i = (\theta_i, \theta_{Fi}, R_i)|i = 1, 2, \ldots, N\}$, where θ_i is a set made up of key model parameters and θ_{Fi} is a set made up of parameters in fault settings. R_i is a trajectory set consisting of various observed variable response trajectories. The average Euclidean distance $d_{ij}(T_c)$ between S_i and S_j (with T_c time scale post-disturbance trajectory) can be calculated with following formula:

$$d_{ij}(T_c) = \sqrt{\frac{\sum\limits_{t=1}^{T_c} \sum\limits_{s=1}^{n} \left(R_i^s - R_j^s\right)^2}{n \cdot T_c}} \tag{1}$$

where n is the number of trajectory kinds defined in R_i.

From Eq.(1), the similarity evaluation index cannot reflect neither the effect of different dimensionality of different time series, nor the relationship between sampling points of trajectories. Hence, correlation coefficient is considered for similarity evaluation index computation in this paper, instead of the Euclidean distance based similarity evaluation index. Moreover, cluster analysis based method computes distances of each element of two clustered sets in every cluster step, whose computing burden increases sharply when trajectory set is large in scale.

Considering requirements of the non-Euclidean distance scenario and computing efficiency, this paper proposes a correlation coefficient index based forward and backward cluster method. The proposed cluster algorithm uses the following formula to calculate the correlation coefficient r of different trajectories to describe similarities among trajectories. Hence, the drawback caused by dimensionality difference is eliminated. Meanwhile, the correlation coefficient is in [0], [1], which has a good feature in consensus.

$$r_{ij}(T_c) = \frac{1}{n}\sum_{s=1}^{n} \frac{Cov(R_i^s, V_j^s)}{\sqrt{Var\left(R_i^s\right) Var\left(R_j^s\right)}}$$

$$Cov(R_i^s, R_j^s) = \sum_{t=1}^{T_c} \left(R_{i,t}^s - \bar{R}_i^s\right)\left(R_{j,t}^s - \bar{R}_j^s\right),$$

$$Var\left(R_{i,t}^s\right) = \sum_{t=1}^{T_c} \left(R_{i,t}^s - \bar{R}_i^s\right)^2, \tag{2}$$

where, $\bar{R}_i^s$ and $\bar{R}_j^s$ are mean value of trajectory R_i^s and R_j^s respectively.

On this basis, a forward and backward cluster algorithm is applied to improve computation efficiency. It classifies trajectories into the same class with the similarity index less than threshold h and into different classes with the similarity index larger than threshold h.

Further, the forward and backward cluster algorithm can be applied with the given N samples $\{S_i = (\theta_i, \theta_{Fi}, R_i)|i = 1, 2, \ldots, N\}$. It assumes that $M_1 = \{S_i|i = 1, 2, \ldots, N\}$ is the classification set. $M_2 = \emptyset$ and $M_3 = \emptyset$ are archive set and typical pattern set respectively. The similarity threshold is set as h. First, a sample S_i in set M_1 is selected randomly as the initial typical pattern, which is then settled in typical pattern set M_3 and deleted from M_1. Then the forward cluster can be started, and it has following procedures.

1) Calculate correlation coefficients between the selected typical pattern and all samples in the classification set M_1 with Eq.(2).
2) Find samples with correlation coefficients higher than threshold h in classification set M_1 and move them to archive set M_2.
3) Find the sample with lowest correlation coefficient in the remaining samples of classification set M_1 and move it to typical pattern set M_3.
4) If classification set is not none, go back to step (1). Otherwise, the forward cluster is finished.

After the forward cluster step, correlation coefficient among samples in typical pattern set M_3 is always less than threshold h and any sample in archive set M_2 has at least one relative sample in typical pattern set M_3 with correlation coefficient higher than h.

Backward cluster step is then started. Each sample in the archive set M_2 is compared with that in the typical pattern set M_3 by correlation coefficient and then it is archived into

the relative pattern class with highest correlation coefficient in the typical pattern set M_3.

B. CONSTRUCTION OF TYPICAL PARAMETERS MATCHING DATABASE

After the forward and backward cluster method is implemented, the typical parameters matching database can be constructed. The construction and update process are presented as follows.

1) ***Pattern extraction and typical parameters matching database construction:*** N samples in the classification set M_1 can be reduced to M typical patterns in the typical pattern set M_3 by the forward and backward cluster method. To construct the typical parameters matching database, samples in the typical pattern set M_3 is referred. Given a sample $S_i = (\theta_i, \theta_{Fi}, R_i)$ in M_3, R_i is seen as the typical response trajectories $R_{pattern,i}$ and mean value of sample parameters in the typical pattern class θ_i is seen as the typical parameters $\theta_{pattern,i}$. Finally, the typical response trajectories $R_{pattern,i}$ and typical parameters $\theta_{pattern,i}$ consist of the typical parameters matching database $D = \{(R_{pattern,i}, \theta_{pattern,i})|i = 1, 2, \ldots, M\}$.

2) ***Updates of typical parameters matching database:*** The constructed typical parameters matching database should be able to update with development of actual scenarios. Given a newly collected sample S_{new}, calculate the correlation coefficient values between the new sample and all typical patterns in database D. If there exists the correlation coefficient larger than threshold h, then the new sample is added to the pattern in database D with largest correlation coefficient. If no correlation coefficient exceeds the threshold h, then the new sample is added to the database D as a new typical pattern.

Specifically, the typical parameters matching database construction and update process is illustrated in Fig.2.

III. COMBINED METHOD FOR ONLINE PARAMETER IDENTIFICATION

With initial value given by the estimation process, the gradient decent method then can be applied for further parameter correction. In this section, the gradient decent method and the implementation of the proposed combined method are presented.

A. GRADIENT DECENT METHOD FOR PARAMETER CORRECTION

To realize gradient decent method, an effective index that evaluate the trajectory difference is important, which can evaluate the performance of calculation and guide adjusting relative parameters. In this paper, the comprehensive evaluation index is calculated with following formula, which is proposed by referring mean average percentage error (MAPE)
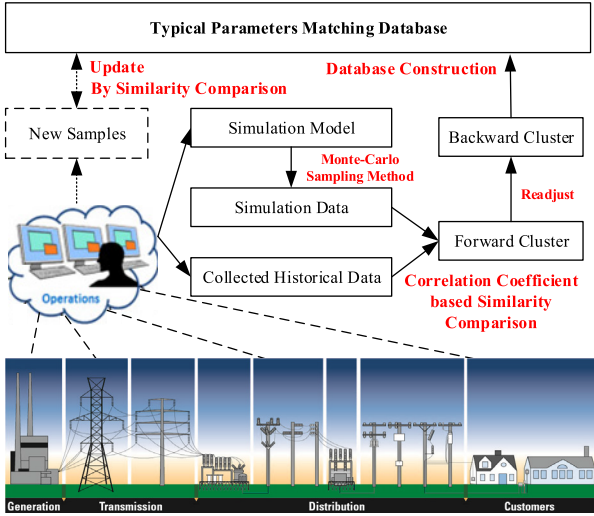
FIGURE 2. Illustration of typical parameters matching database construction and update process.

index.

$$F(\boldsymbol{\theta}_i) = \frac{1}{n \cdot T} \cdot \sum_{s=1}^{n} \sum_{t=1}^{T} \frac{|R_s(\boldsymbol{\theta}_i, t) - R_{s,\text{real}}(\boldsymbol{\theta}_0, t)|}{R_s^N} \quad (3)$$

where, T and n are length of trajectory data and number of referred trajectories. $R_s(\boldsymbol{\theta}_i, t)$ is the s-th recorded trajectory value at time t in the i-th parameter identification step. $R_{s,\text{real}}(\boldsymbol{\theta}_0, t)$ is the s-th actual trajectory value at time t. R_s^N is the reference value for the s-th trajectory data. It describes the performance of gradient decent method in parameters correction, compared with actual data.

With the comprehensive evaluation index, the gradient decent value for each parameter then can be determined by mathematical calculation with following formula.

$$\nabla F\left(\theta^i\right) = \lim_{\varepsilon \to 0}$$

$$\frac{F\left(\theta^0, \ldots, \theta^i + \varepsilon, \ldots, \theta^n\right) - F\left(\theta^0, \ldots, \theta^i - \varepsilon, \ldots, \theta^n\right)}{2\varepsilon} \quad (4)$$

where $\nabla F\left(\theta^i\right)$ means the performance comprehensive evaluation index gradient value of i-th parameter of the parameter set θ. Further the parameter correction formula can be put forward with following form.

$$\begin{cases} d\theta^i = \dfrac{F\left(\theta^0, \ldots, \theta^n\right)}{\nabla F\left(\theta^i\right)} \\ \theta^i = \alpha\left(\theta^i - d\theta^i\right) \end{cases} \quad (5)$$

where, $F\left(\theta^0, \ldots, \theta^n\right)$ is the comprehensive evaluation index value and α is the length of each iterative step. After iterative calculation and adjusting parameters, the comprehensive evaluation index could decrease and converge to a certain value, which finally indicates termination of the parameter correction process.

B. PROPOSED COMBINED METHOD FOR ONLINE PARAMETER IDENTIFICATION

In the combined parameter identification method, the patter matching method enables to provide initial parameter values quickly according to post-disturbance response trajectories. After the pattern matching method, the gradient decent method can further correct the provided initial parameters values according to the dynamic features reflected by post-disturbance trajectories. Hence, the better identification result and computation speed of the gradient decent method is expected with better initial values provided by pattern matching method.

In all, the proposed combined parameter identification method comprises following steps, shown as Fig.3.

1) **Initialize:** load the constructed typical parameters matching database $\boldsymbol{D} = \{(\boldsymbol{R}_{pattern.i}, \boldsymbol{\theta}_{pattern.i}) | i = 1, 2, \ldots, M\}$. Set maximum correction steps t_{max} and correction step length α.

2) **Online detect:** observe system operation status. If disturbance is detected, collect the post-disturbance trajectories $\boldsymbol{R}_m$ and relative disturbance information.

3) **Pattern matching:** calculate the correlation coefficients between collected data $\boldsymbol{R}_m$ and typical trajectory patterns $\boldsymbol{R}_{pattern.j}$ in the database. Select the largest correlation coefficient r_{mj} together with its relative typical pattern $\boldsymbol{D}_j$. Take the typical parameters $\boldsymbol{\theta}_{pattern.j}$ of $\boldsymbol{D}_j$ as the initial parameter values.

4) **Parameter correction:** Take $\boldsymbol{\theta}_{pattern.j}$ as the initial parameter value $\boldsymbol{\theta}_0 = \boldsymbol{\theta}_{pattern.j}$. Do iterative parameter corrections according to gradient decent method until maximum correction step is achieved.
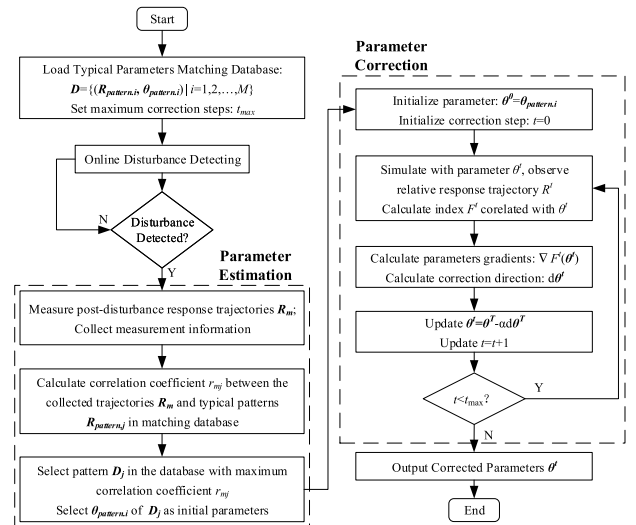

FIGURE 3. Flow diagram of the combined parameter identification method implementation.

IV. CRITICAL HVDC MODEL PARAMETERS DETERMINATION

To apply the proposed combined parameter identification method for HVDC model, determining HVDC model critical

parameters is the key step. In this section, components of HVDC model is presented and then sensitivity analysis is used to determine critical parameters of HVDC model.

A. COMPONENTS OF HVDC MODEL

A HVDC system is usually made up of convertor stations, direct current (DC) transmission lines, transformers, control equipment, etc. To emulate effects of HVDC on power system electromechanical transients, PSASP provides a standard HVDC model, named with type 5 HVDC model.

For the type 5 HVDC model, the converter model is described with steady state model considering requirements of computation efficiency. Meanwhile, transmission lines are modelled with differential equations, where dynamic features of DC transmission line can be considered. Hence, the convertor and DC transmission line model can be determined with following equations.

$$
\begin{aligned}
V_d &= V_{do} \cos \alpha - \frac{3}{\pi} X_c I_d B \\
V_{do} &= \frac{3\sqrt{2}}{\pi} BT E_{ac} \\
\frac{dI_d}{dt} &= \frac{1}{L_{si} + L_l + L_{sj}} \\
&\quad \times \left(V_{oi} \cos \alpha - V_{oj} \cos \beta - \left(R_{ci} + R_l + R_{cj} \right) I_d \right)
\end{aligned}
\tag{6}
$$

where, V_d and I_d are DC voltage and current respectively. E_{ac} is effective value of line voltage at the alternative current (AC) side. T is the transformer turns ratio. B is number of convertor series. L_{Si}, L_{Sj} and L_l are inductance at rectifier, inverter and DC transmission line. R_{si}, R_{sj}, and R_l are resistance at rectifier, inverter and transmission line. α and β are firing and extinction angles at rectifier and inverter side.

In actual, parameters affecting dynamic features of HVDC model mainly lie in control system [20]. Detailed components of HVDC control system are illustrated in Fig.4.

In the control system, there are 9 control modules. Under voltage disturbances caused by short circuit at AC side, there are 4 main control modules taking effects, including voltage dependent current order limiter (VDCOL) module, current control module, commutation failure prediction module, and voltage control module. Hence, critical parameters affecting dynamic features of HVDC model are searched among these four control modules.
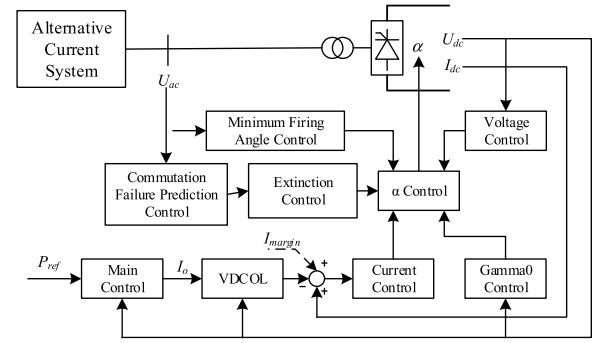

FIGURE 4. Component modules of HVDC control system.

B. SENSITIVITY ANALYSIS FOR CRITICAL PARAMETERS DETERMINATION

Model parameter sensitivity can reflect the relationship between model response features and parameters. It can be obtained by calculating the partial derivative of model response features to parameters. Hence, sensitivity of j-th parameter θ_j to i-th model response feature at time k can be described with following formula, (7) as shown at the bottom of the page, where, m is the number of model parameter candidates.

HVDC model is usually with strong nonlinearity, which makes it hardly possible to calculate parameter sensitivity by analytical sensitivity analysis methods. Hence, the mathematical sensitivity analysis method is adopted in this paper. The i-th model response feature $Y_{i+} = \{y_i(\theta_1, \ldots, \theta_j+\Delta\theta_j, \ldots, \theta_m, k)|k = 1, 2, \ldots, T\}$ and $Y_{i-} = \{y_i(\theta_1, \ldots, \theta_j - \Delta\theta_j, \ldots, \theta_m, k)|k = 1, 2, \ldots, T\}$ are collected with small disturbances $+\Delta\theta_j$ and $-\Delta\theta_j$ on parameter θ_j respectively. The calculation formula for parameter sensitivity is shown as (8), shown at the bottom of the page, where, θ_{j0} is the given value of θ_j, and y_{iN} is the rated value of i-th model response feature.
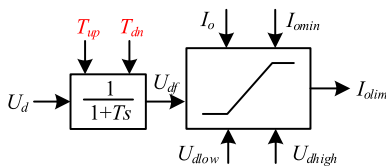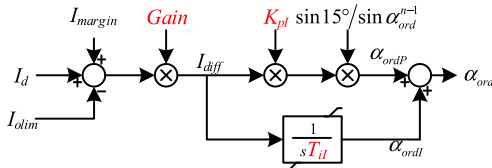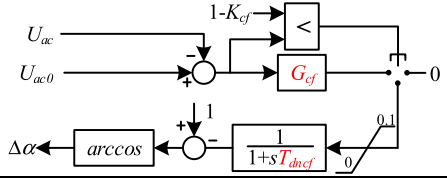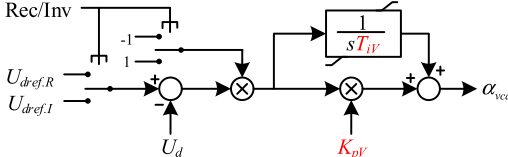
Voltage at rectifier side, voltage at inverter side and DC current on transmission lines are used to form the average sensitivity A_j. Because they are measurable and can demonstrate HVDC model dynamic characteristics.

$$
\begin{aligned}
A_j = \frac{1}{3T_c} \sum_{k=1}^{T_c} &\left(\left| \frac{\partial \left[V_{rec.i}\left(\boldsymbol{\theta}, k \right)/V_N \right]}{\partial \left[\theta_j/\theta_{j0} \right]} \right| \right. \\
&+ \left| \frac{\partial \left[V_{inv.i}\left(\boldsymbol{\theta}, k \right)/V_N \right]}{\partial \left[\theta_j/\theta_{j0} \right]} \right| \\
&\left. + \left| \frac{\partial \left[I_d\left(\boldsymbol{\theta}, k \right)/I_N \right]}{\partial \left[\theta_j/\theta_{j0} \right]} \right| \right)
\end{aligned}
\tag{9}
$$

$$
\frac{\partial y_i\left(\boldsymbol{\theta}, k \right)}{\partial \theta_j} = \lim_{\Delta\theta_j \to 0} \frac{y_i\left(\theta_1, \ldots, \theta_j + \Delta\theta_j, \ldots, \theta_m, k \right) - y_i\left(\theta_1, \ldots, \theta_j - \Delta\theta_j, \ldots, \theta_m, k \right)}{2\Delta\theta_j}
\tag{7}
$$

$$
\frac{\partial \left[y_i\left(\boldsymbol{\theta}, k \right)/y_{iN} \right]}{\partial \left[\theta_j/\theta_{j0} \right]} = \lim_{\Delta\theta_j \to 0} \frac{\left[y_i\left(\theta_1, \cdots, \theta_j + \Delta\theta_j, \cdots, \theta_m, k \right) - y_i\left(\theta_1, \cdots, \theta_j - \Delta\theta_j, \cdots, \theta_m, k \right) \right]/y_{iN}}{2\Delta\theta_j/\theta_{j0}}
\tag{8}
$$

TABLE 1. Sensitivity analysis of critical parameters in HVDC control modules.

Control Module Name	Transfer Function Form of Control Module	Parameter Name	Sensitivity Value
VDCOL		T_{up}	0.962227
		T_{dn}	0.627573
Current Control		$Gain$	4.56526
		K_{pI}	1.13001
		T_{iI}	4.66921
Commutation Failure Prediction Control		G_{cf}	12.6753
		T_{dncf}	2.35572
Voltage Control		K_{pv}	0.12848
		T_{iV}	4.37164

If the average sensitivity index A_j is large, the parameter θ_j should be selected as the critical parameter for further identification. Top 11 parameters are list in Table 1. Hence, all these parameters are considered as critical parameters of HVDC model. And all these parameters are used in tests of the proposed parameters identification method.

V. CASE STUDY

In this section, validations of the proposed combined parameter identification method on HVDC model is implemented. EPRI-36 test system is used as the testbed. Specifically, parameters in VDCOL control, current control, commutation failure control and voltage control sub-modules are concerned for identification.

A. SAMPLE GENERATION FOR TYPICAL PARAMETERS MATCHING DATABASE

Samples are generated by Monte-Carlo method based on PSASP software. Critical HVDC model parameters are assumed to follow uniform distribution in a given range, shown in Table 2.

In addition to critical model parameters variation, the fault setting parameters variation is also considered. In simulation, the fault is assumed as the three-phase short circuit happened at bus 13. The fault takes place at 0.1s and the fault ending time ranges in 0.19s and 0.25s following uniform distribution.

**TABLE 2.** Critical parameters of HVDC model and typical values.

HVDC Control Sub-module	Parameter Type	Typical Value	Variation Range
VDCOL Control	T_{up}	0.03	[0.01, 0.05]
	T_{dn}	0.015	[0.01, 0.02]
	$Gain$	30	[25, 40]
Current Control	K_{pI}	3.44	[2, 4]
	T_{iI}	0.009	[0.006, 0.015]
Commutation Failure Control	G_{cf}	0.15	[0.1, 0.015]
	T_{dncf}	0.02	[0.01, 0.03]
Voltage Control	K_{pv}	26	[20, 40]
	T_{iV}	0.0005	[0.0002, 0.0015]

The fault impedance is assumed to follow uniform distribution in [0, 0.05] p.u.

The simulation is carried out by a computer with Inter(R) Core i5-5200U and 8G cache. The simulation time and computation step are set as 2s and 0.01s respectively. Finally, 5500 samples are generated, where 5000 samples are used for typical parameters matching database construction and 500 samples are used for performance test.

B. DEMONSTRATION OF CONSTRUCTED DATABASE

According to the correlation coefficient based forward and backward cluster method, the forward classification process determines the number of typical patterns. To show the effects
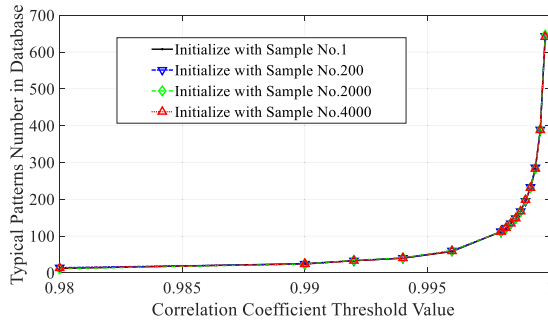
FIGURE 5. Variation of typical patterns number in database with increase of correlation coefficient threshold value.

of the proposed cluster method, the relationship between typical pattern number in database and correlation coefficient threshold is illustrated in Fig.5.

Four scenarios with different initialization samples are presented in figure above. It indicates that the typical pattern number increases along with the increase of threshold value. In addition, different initialization samples cause few effects on typical patterns number in the database when threshold value is determined. It means that the randomly selected initial sample would make no effects on typical pattern cluster results.

C. PERFORMANCE OF HVDC MODEL PARAMETERS IDENTIFICATION BASED ON PROPOSED COMBINED METHOD

In scenarios test settings, the correlation coefficient threshold is set as 0.999 and total 194 typical patterns are obtained, which finally forms the typical parameters matching database. The features used for pattern matching include post-disturbance HVDC voltage and current trajectories with 50-cycle-length measurements. The correction step length is set as 0.5 and the maximum correction step is set as 5.

(1) Performance of single test scenario: Take a sample in test set as example. Correlation coefficients between the tested sample and typical patterns in the constructed matching database is shown in Fig.6.
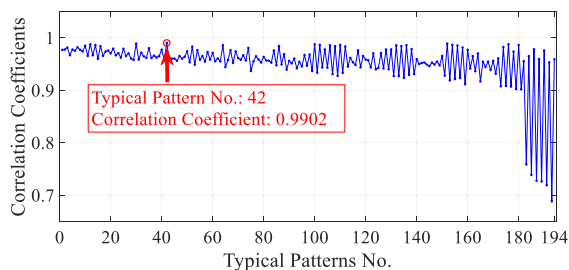
FIGURE 6. Correlation coefficients between test sample and typical patterns in typical parameters matching database.

From Fig.6, it can be seen that the No.42 typical pattern in the matching database has the most similar features with the test sample, where the correlation coefficient is 0.9902.

Hence, the No.42 typical pattern is selected as the reference pattern and its parameters are used as the initial parameters values for gradient decent method.

Further, the gradient decent method is applied for initial parameters correction. After the correction process, the identified parameters and actual parameters are list in Table 3. It can be seen from table that the parameter correction process of the proposed combined method takes effects, which is more closed to actual value than the initial value provided by pattern matching.

TABLE 3. Performance comparison of pattern matching and proposed combined method.

| Parameter Type	Actual Value	Initial Value by Pattern Matching	Identified Value by Proposed Method
T_{up}	0.0447	0.0319	0.0417
T_{dn}	0.0187	0.0155	0.0170
$Gain$	38.0114	33.2408	38.4022
K_{pI}	3.7349	3.0974	3.5884
T_{iI}	0.0138	0.0109	0.0162
G_{cf}	0.2301	0.1823	0.2183
T_{dncf}	0.0273	0.0210	0.0246
K_{pv}	37.3486	30.9744	36.3146
T_{iV}	0.0013	0.0009	0.0011

Moreover, the comparison of post-disturbance HVDC model response trajectories between actual parameters and identified parameters are presented in Fig.7. These response trajectories indicate that the proposed method has good performances in parameter identification accuracy.

(2) Overall performance under multiple test scenarios: To show the effects of proposed combined method, 500 generated test scenarios are all applied for validation. As comparison, PSO method is also implemented under the same test scenarios, which aims to minimize the comprehensive evaluation index. The population quantity, maximum iteration times, inertia weight, learning factor 1 and 2 are set as 50, 100, 0.8, 0.5 and 0.5 respectively. Table 4 shows overall performances of proposed combined method and PSO method in accuracy and computation speed.

In Table 4, it indicates that PSO method is much better than the proposed method in precision, while it is far behind in computing speed. It is believed that the proposed method is more suitable for online parameter identification application

TABLE 4. Performance index comparison between proposed method and PSO method.

Method Type	Mean Value	Minimum Value	Maximum Value	Average Computing Time
Proposed Method	0.0145	0.001	0.0619	5.96s
PSO Method	8.54×10^{-4}	2.93×10^{-5}	0.0052	26.9min
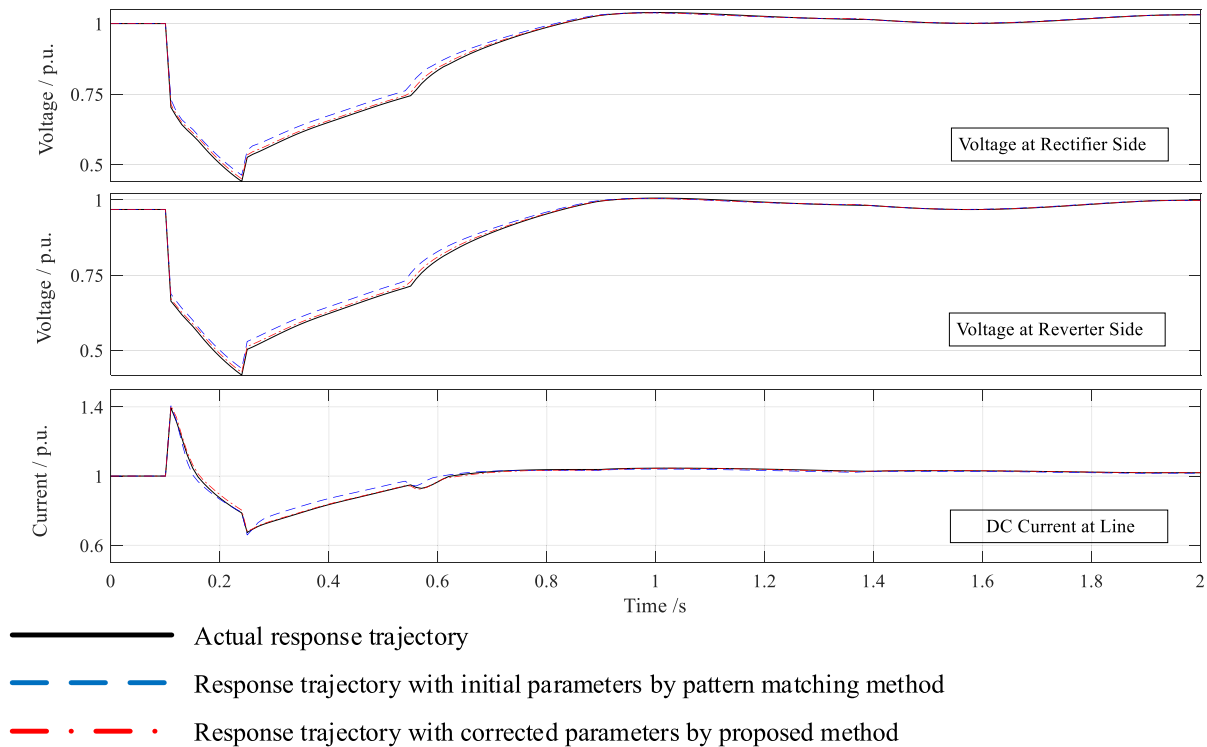
FIGURE 7. Response trajectories comparison by actual, initial, and corrected model parameters.
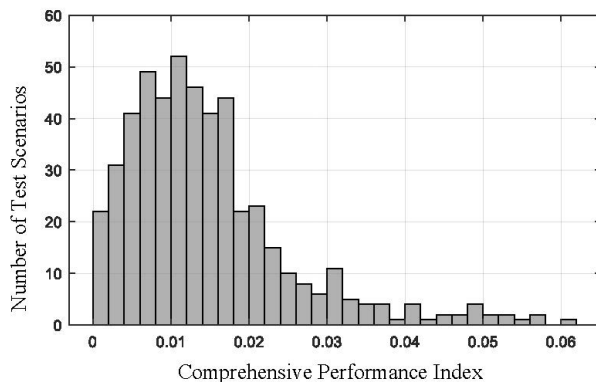
FIGURE 8. Number of test scenarios distribution related to comprehensive evaluation index.

because it reaches acceptable accuracy under limited computing time.

To be specific, the average comprehensive evaluation index is only 0.0145 and the maximum index is 0.0619 for the proposed method, which means the error of simulated response trajectories is only about 1% of HVDC system rated variables and the maximum error is not over 6.2% fitting accuracy. The average computing time is 5.96s, which is in level of seconds, satisfying the requirements of online parameters identification. In Fig.8, comprehensive evaluation index distribution condition of the proposed method is presented, which shows that most test cases concentrate on range (0,0.02].

VI. CONCLUSION

This paper proposes an online parameter identification method by combined estimation and correction method. Specifically, the estimation process is realized by pattern matching, and the correction process relies on gradient decent method. A correlation coefficient based forward and backward cluster method is presented for typical parameter matching database construction and fast update. With the proposed combined parameter identification method, the local optimum problem of previous gradient decent method can be handled. A comprehensive evaluation index is also proposed for gradient decent method to evaluate effects of parameter identification. Tests on typical HVDC models show effectiveness of the proposed combined method in computation speed and accuracy. In future, the proposed combined parameter identification method can be extended to more application scenarios.

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