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RESEARCH ARTICLE

Parameter Identification of SVG Using Multilayer Coarse-to-Fine Grid Searching and Particle Swarm Optimization

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ABSTRACT Accurate model parameters of Static Var Generator (SVG) play an essential role in regulating bus voltage profiles of power grid with increased penetration of renewable energy under various contingencies. Aiming at addressing the known issues of low identification accuracy and long computation time faced by the traditional SVG parameter identification methods, this paper presents a multi-layer coarse-to-fine grid searching approach for calibrating SVG dynamic model parameters using particle swarm optimization. First, actual measurement data is collected through SVG-RTDS testbeds under various conditions, which is compared with transient stability simulation results to check for model accuracy. Then, nonlinear trajectory sensitivity analysis is performed using segmented curves to identify potential bad model parameters. Next, a multi-layer coarse-to-fine grid searching mechanism is used to narrow the parameter searching space, before particle swarm algorithm optimization is used for more precise identification of parameters. By comparing the identification results obtained by the traditional identification methods and the proposed approach via comprehensive case studies, it is found that the proposed coarse-to-fine parameter identification method achieved higher accuracy and faster computational speed.

INDEX TERMS SVG controller, parameter identification, nonlinear sensitivity, particle swarm optimization.

NOMENCLATURE

V	The voltage output of SVG.
V_{REF}	The reference voltage of SVG.
V_{SCS}	The auxiliary signal of SVG.
V_T	The system voltage.
I_S	The current output of SVG.
T_1	The time constant of the filter and loop of measurement.
T_2	The first-order lead constant time.
T_3	The second-order lag time constant respectively.
T_4	The second-order lead time constant.
T_5	The third-order lag time constant.
T_P	The proportional link time constant.
T_S	The delay time of SVG response.
K_P	The gain of SVG.
K_i	The gain of the integration module.
K_d	The slope of the V-I characteristic curve.
X_T	The equivalent reactance between the SVG and the power system.
V_{MAX}	The upper limit of the voltage limiter.
V_{MIN}	The lower limit of the voltage limiter.
I_{CMAX}	The maximum capacitive current.
I_{LMAX}	The maximum inductive current.
α_i	The independent variable of trajectory sensitivity.
y_i	The dependent variable of trajectory sensitivity.

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y_{i0}	The model output when the parameter value α_i equal to α_{i0}.
$\Delta\alpha_i$	The change value of α_i.
$\bar{Q}$	The reactive power track sensitivity.
$\bar{I}$	The current track sensitivity.
$\bar{U}$	The voltage track sensitivity.
N	The number of sampling.
Q_0	The initial value of the reactive power track sensitivity.
I_0	The initial value of the current track sensitivity.
U_0	The initial value of the voltage track sensitivity.
Q_1	The output when the reactive power value increased by 5% on the basis of the initial value.
I_1	The output when the current value increased by 5% on the basis of the initial value.
U_1	The output when the voltage value are increased by 5% on the basis of the initial value.
E_Z	The result of error calculation.
t_0	The starting time of error calculation.
t_1	The ending time of error calculation.
Q_{base}	The measured reactive power data of RTDS.
Q_{test}	The simulated reactive power data of BPA.
w	The inertia weight.
$c1, c2$	The learning factor.
$r1, r2$	The uniform distribution between (0,1) as random numbers.
V_i	The velocity of the particle in each dimension.
$V_{\max}$	The maximum velocity that the particle can reach.

I. INTRODUCTION

With the increased penetration of renewable generation, growing electricity loads and fast development of grid infrastructure, the modern power system in mainland China is facing critical issue of reactive power shortage, which may lead to growing risks of voltage instability [1]. The Flexible AC Transmission System (FACTS) provides a number of technical means to enhance the security and stability of the grid. As an advanced reactive power compensation device, Static Var Generator (SVG) is one of the core members of the FACTS family being widely used in many fields such as transmission network, distribution network and integration of renewable energy generation [2], [3]. If designed and operated properly, SVG can compensate for fluctuating loads, harmonics, and power factor to reduce power loss and improve power quality, to deal with the increased dynamic and stochastic behavior of the modern power system [4]. The level of SVG model accuracy plays an important role in affecting the reliability of power system simulations, and thus directly affects the quality of power grid planning, design and integration of wind/solar farms, grid security and stability, etc. However, most manufacturers are unable to provide accurate SVG models and the corresponding parameters for grid planning and operational studies due to intellectual property protection or lack of testing techniques in practice [5]. To ensure optimal design and operation of SVG in the bulk power system, effective methods for accurate parameter identification of SVG models are urgently needed.

Traditional methods, e.g., least square-based algorithms, for parameter identification demonstrate satisfactory performance for linear control system; however, for more complex and highly nonlinear systems, the performance of such methods deteriorates, leading to large identification errors [6]. With the rapid development and evolvement of intelligent searching algorithms such as chicken swarm optimization (CSO), genetic algorithm (GA), deep reinforcement learning (DRL) and others, new methods have emerged to tackle with the problem of parameter identification and find optimal parameter sets of complex systems under various conditions. In fact, previous research efforts were reported to achieve this goal. In [7], the authors presented a PSO-based algorithm to calibrate SVG model parameters for both low-wind-speed and high-wind-speed conditions in wind farms considering random characteristics of wind farm. Parameter identification errors caused by wind speed fluctuation were effectively reduced; however, this method suffers from a large searching space, affecting the total computational speed. The authors of [8] proposed an improved CSO-based method for identification of Static Var Compensator parameters, using local sensitivity and intelligent optimization theory. Although the CSO algorithm is similar to PSO, it heavily depends upon an accurate estimation of parameter range, which can take many iterations of searching and require long computation time. In [9], a RTDS-based hardware-in-the-loop testbed is used for parameter identification, which can successfully identify key controller parameters. However, the adaptability of this method is poor given that there are many parameters in each controller and the interaction among various parameters was not considered, affecting the overall effectiveness and efficiency [9]–[12]. The SVG controller consists of many parameters and the searching range of each parameter is difficult to determine; thus, it may take much more time to obtain the optimal parameter set if searching a large parameter range. However, when the parameter range is set too small, it can lead to situations where the exact parameters cannot be identified [13], [14]. Therefore, it is essential to screen those parameters with higher sensitivity with respect to SVG power outputs, and select a rational range of parameters before applying parameter identification algorithms. Moreover, traditional methods typically use the entire simulation curves for identifying model parameters, which ignore interactions among various parameters and may yield situations where the parameters cannot be identified correctly.

In order to resolve the above issues, this paper presents a novel method of SVG parameter identification using a multilayer, coarse-to-fine grid searching framework with particle swarm optimization. First, it compares the simulation results obtained from the BPA software and the actual measurements obtained from the RTDS testbed. Then, key parameters with high sensitivity are selected through nonlinear trajectory sensitivity analysis conducted on segments of reactive power curves of SVG [15]. Sensitivity information is clustered into segments, which are used to calibrate those model parameters that are highly sensitive in different segments. In this way, narrower ranges of parameter searching space can be determined before applying PSO algorithms for precise parameter identification, which can effectively reduce the complexity and overcome the abovementioned issues. This method can be used for improving SVG parameter identification accuracy and efficiency, and ensuring high quality transient stability simulation of bulk power systems.

The remainder of this paper is organized as follow. Section II introduces the test systems for SVG model parameter identification, including the hardware-in-the-loop testbed, simulation models and the control logic of SVG. Section III presents the trajectory sensitivity analysis method for identifying sensitive parameters in different segments. In Section IV, detailed characteristics of parameters are analyzed and the proposed coarse-to-fine grid searching method is presented in Section V. In Section VI, comprehensive case studies are used to verify the effectiveness of the proposed approach. Finally, conclusions are drawn in Section VII with future work identified.

II. TEST SYSTEMS FOR SVG PARAMETER IDENTIFICATION

A. RTDS HARDWARE-IN-THE-LOOP TESTBED

Real Time Digital Simulator (RTDS) is one of the most popular real-time simulators for power system research and development purposes, designed by the direct current research center of Manitoba, Canada, primarily for real time parallel electromagnetic transient simulation [11]. RTDS can simulate fast transient processes of power system in real time, where the primary system is simulated by mathematical model, and the secondary equipment uses actual controller device. The hardware-in-the-loop (HIL) testbed can be constructed by connecting the physical controller to the bulk power grid model through the I/O interface. HIL testing is equivalent to connecting a physical controller to an actual power system, thus enabling detailed closed-loop physical testing under various operating conditions [12].

In this paper, an actual SVG device is connected to the real-time closed-loop testbed using the RTDS platform. A single-machine-infinite-bus system model is created to represent the power grid, shown in Fig.1. The system consists of an infinite power supply, a 220/35 kV transformer, a parallel transmission line, a SVG device, and a switchable reactance. The switchable reactance is used to simulate a three-phase-to-ground short-circuit fault at bus B1. The purpose of installing the SVG is to maintain constant voltage profiles at bus B1. Three-phase-to-ground faults with various switching reactance are applied at bus B1 by switching off the reactance to generate transient response trajectories. Transient voltage profiles, reactive power curves and the current curves are recorded for model parameter identification purposes.

In real-world application, the SVG equipment functions like a black box with little knowledge of true parameters. RTDS provides a promising way of simulating high-fidelity

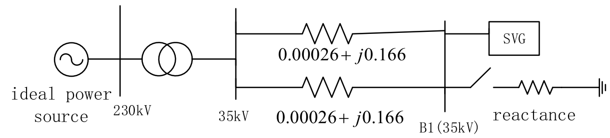


FIGURE 1. Test system setup.

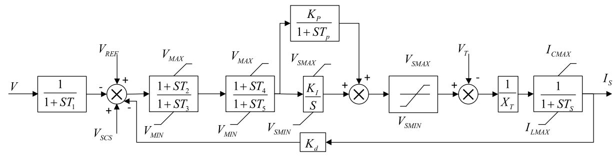


FIGURE 2. Control block diagram of SVG.

grid disturbances [10]. In this work, power grid models are created in BPA software to simulate the dynamic performance of the SVG, the transient trajectory of which is then compared with the one obtained from RTDS as actual measurements. The objective of SVG parameter identification is to minimize the mean square error (MSE) of the two reactive power trajectories obtained from BPA simulation and RTDS actual measurements collected at the point of connection.

B. SVG CONTROLLER MODEL

The control block diagram of the SVG controller for parameter identification is shown in Figure 2 [15].

In the SVG model, V is the voltage output; V_{REF} is the reference voltage; V_{SCS} is the auxiliary signal; V_T is the system voltage; I_S is the current output; T_1 represents the time constant of the filter and loop of measurement; T_2 and T_3 are the first-order lead constant time and the second-order lag time constant, respectively; T_4 and T_5 are the second-order lead time constant and the third-order lag time constant; T_P is the proportional link time constant; T_S is the delay time of SVG response; K_P is the gain; K_i is gain of the integration module; K_d is the slope of the V-I characteristic curve and X_T is the equivalent reactance between the SVG and the power system. There are also limiters in the control block diagram, including: V_{MAX} - the upper limit of the voltage limiter, V_{MIN} - the lower limit of the voltage limiter, I_{CMAX} - the maximum capacitive current, I_{LMAX} - the maximum inductive current. The equation for calculating the limits of the proportional integral block, V_{SMAX} and $V_{SMIN,}$ is given in Eq. (1):

$$\begin{aligned} V_{SMAX} &= V_T + X_T * I_{CMAX} \\ V_{SMIN} &= V_T - X_T * I_{LMAX} \end{aligned} \tag{1}$$

From the control block diagram of SVG, the initial parameter set to be identified can be determined as a vector:

$$[T_1, T_2, T_3, T_4, T_5, T_S, T_P, K_P, K_I, K_D, \\ V_{MAX}, V_{MIN}, I_{CMAX}, I_{LMAX}]$$

III. TRAJECTORY SENSITIVITY ANALYSIS

Trajectory sensitivity analysis provides an effective way to quantify the impact of independent variables on dependent variables in the nonlinear dynamic system. The effect of each parameter change on the system outputs can be obtained by analyzing the trajectory sensitivity of the parameters. A high value of trajectory sensitivity indicates that the parameter has larger influence on the system, while a low trajectory sensitivity indicates that the parameter has smaller influence. For a dynamical system, trajectory sensitivity is calculated using the following equation:

$$S_{\alpha_i}(t) = \frac{\frac{y_i(\alpha_{i0}+\Delta\alpha_i,t)-y_{i0}(\alpha_{i0},t)}{y_{i0}(\alpha_{i0},t)}}{\Delta\alpha_i/\alpha_{i0}} \tag{2}$$

In Eq.(2), α_i is the independent parameter; y_i is the dependent variable; y_{i0} is model output when the parameter value α_i equal to α_{i0}; $\Delta\alpha_i$ stands for the change value of α_i. In practice, it is difficult to draw an effective conclusion through the observation of the trajectory sensitivity, so the trajectory sensitivity is defined as the average of the absolute values over a period of time, given in Eq. (3), where N is the number of sampling points.

$$S = \frac{1}{N}\sum_{t=1}^{N}\left|S_{\alpha_i}(t)\right| \tag{3}$$

For SVG controllers connected to a single-machine-infinite-bus system, the following steps are used to calculate the sensitivity of parameter trajectory.

1) Set up a simulation system to determine the parameters to be identified, the initial values of which can be taken from the SVG's technical manual; if the manual does not provide the corresponding parameters, then use the typical parameter values of SVG as the initial values.

2) Calculate the power flow for the system, set up a three-phase-to-ground short-circuit fault, perform a transient stability simulation, and record the output variables of the SVG device, including reactive power, current and voltage trajectories.

3) Increase the values of the selected parameters by 5%, while keeping all other parameters constant and repeat the same procedure in Step 2) to obtain simulated curves of reactive power, current and voltage for each perturbed parameter. Sensitivities of each parameter with respect to reactive power, voltage and current are calculated as follows.

$$\begin{cases} \overline{Q} = \dfrac{1}{N}\sum_{N=1}^{N}\left|\dfrac{Q_1(t)-Q_0(t)}{0.05*Q_0(t)}\right| \\ \overline{I} = \dfrac{1}{N}\sum_{N=1}^{N}\left|\dfrac{I_1(t)-I_0(t)}{0.05*I_0(t)}\right| \\ \overline{U} = \dfrac{1}{N}\sum_{N=1}^{N}\left|\dfrac{U_1(t)-U_0(t)}{0.05*U_0(t)}\right| \end{cases} \tag{4}$$

where $\overline{Q}, \overline{I}, \overline{U}$ stand for reactive power sensitivity, current sensitivity and voltage sensitivity, respectively; N is the number of sampling. Q_0, I_0, U_0 represent the initial values of the reactive power, current and voltage. Q_1, I_1, U_1 stand for the corresponding values of reactive power, current and voltage with the perturbed parameter values.

(4) Sort the sensitivity values of all selected parameters using the above procedure from the largest to smallest. The parameters with higher trajectory sensitivity values are selected for calibration.

IV. ANALYSIS OF PARAMETER CHARACTERISTICS DURING FAULT CONDITIONS

After selecting the key parameters based on the trajectory sensitivity calculation method introduced in Section III, the impact of these parameters on the SVG dynamic characteristics during fault conditions is analyzed. In the traditional process of parameter identification, the performance of parameter identification cannot be guaranteed because of the complex, coupled interaction of various parameters and the large range of parameters. Thus, it is necessary to explore the influence of parameters on the fault characteristic of the system, identify the parameters using various segmented data, improve the identification speed, reduce the influence of other parameters, and determine a proper range of the parameters.

For each parameter to be identified, determine its upper and lower limits and the step size. The parameter changes from the lower limit and increases by the fixed step size until reaching the upper limit. Record the changes of reactive power curve and current curve with respect to parameter changes and observe those sections of the curve with high sensitivity. Then, the detailed influence of each parameter on the fault characteristics is investigated, and the corresponding sections of the simulation result curves are used to identify each SVG model parameter. For the parameters with high trajectory sensitivity, the variation of reactive power curve is analyzed with the simulation results.

Fig. 3 provides an explanatory example, where the entire reactive power curve is divided into four segments to compute the corresponding sensitivity information. Table 1 gives the calculated sensitivity of various parameters for the four segments. The selected parameter candidates are $[T_1, T_2, T_3, T_4, T_5, T_s, K_i, K_d, I_{CMAX}]$. The initial values of the above selected parameters are provided in Table 2. It can be observed that the same parameter change has very different impact on the reactive power curve sections. Thus, using such segmented sensitivity information for calibrating parameters can be very effective.

As can be seen from Table 2, the trajectory sensitivity of the parameters K_P and T_P is small, close to 0. Similarly, the sensitivity values of V_{MAX}, V_{MIN}, I_{LMAX} are zero; therefore, in the subsequent procedure, these parameters are excluded from the candidate list for calibration. For each section of the reactive power curve, identify the parameters with the largest sensitivity values for initial estimation using the coarse grid searching procedure described in the following sections. Thus, the selected parameters for the four sections are marked bold in Table 1.

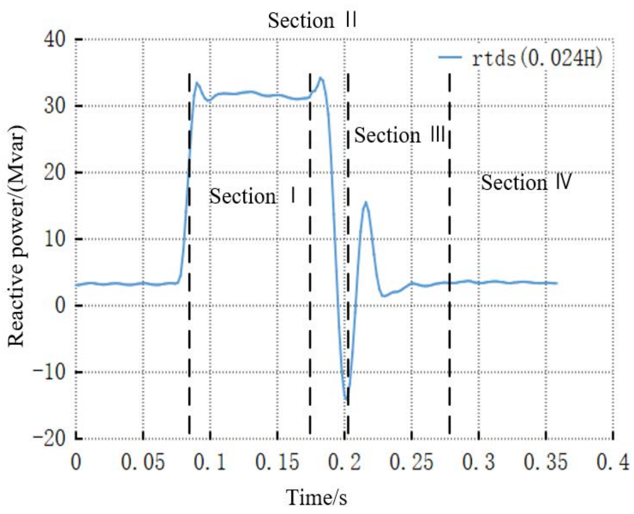


FIGURE 3. Sensitivity information for different sections of the reactive power curve.

TABLE 1. Reactive power sensitivity of each parameter of the SVG controller.

SVG parameters	Sensitivity of section I	Sensitivity of section II	Sensitivity of section III	Sensitivity of section IV
T_1	0	2.231	**6.339**	0.846
T_2	0	**2.356**	10.657	2.185
T_3	0	**2.269**	9.618	1.946
T_4	0	**2.356**	10.657	2.185
T_5	0	**2.263**	9.379	1.915
T_P	0	0.001	0.003	0.0006
T_S	0.084	0.838	**7.258**	1.419
K_P	0	0.001	0.002	0.0001
K_i	0.404	23.143	64.855	**24.575**
K_d	0	1.107	**5.528**	0.988
I_{CMAX}	**1.058**	1.581	2.137	0.236

TABLE 2. The initial value of the SVG controller parameter.

parameter	initial value	parameter	initial value
T_1	0.005	K_p	0.02
T_2	1.00	K_i	999
T_3	1.00	K_d	0.02
T_4	1.00	V_{MAX}	1
T_5	1.00	V_{MIN}	-1
T_p	0.5	I_{CMAX}	1.1
T_S	0.005	I_{LMAX}	1.1

V. PROPOSED PARAMETER IDENTIFICATION ALGORITHM

A. GRID SEARCH

Grid search is an exhaustive method to evaluate all possible discretized parameter values by forming a grid of all possible value combinations and then comparing the model performance of each parameter set before finding the best set with the least curve fitting errors. In the process of model parameter identification, parameter ranges are typically unknown; if the range is set too small, one may not find the true values of parameters. Therefore, the grid search method is used as the initial step to select a large range of parameters so that the true ones can fall inside certain bins in the high dimensional space and the identification speed can be improved. Then, according to the fault characteristics, the piecewise curve is selected to search for the true parameters separately, and the optimized parameter values are obtained using particle swarm method. In this way, the total calculation burden is effectively reduced.

The objective function of SVG model parameter identification is defined as the square error of reactive power curves between the actual measurements of RTDS and the corresponding simulation curve, given in Eq.(5).

$$E(z) = \sum_{t=t_0}^{t=t_1} (Q_{base}(t) - Q_{test}(t))^2 \tag{5}$$

where E_Z is the model error, t_0 is the starting time and t_1 is the ending time of the error calculation, Q_{base} is the measured reactive power obtained from RTDS and Q_{test} is the simulated reactive power data from BPA software.

B. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is an intelligent algorithm that starts from random initial values and searches for the optimal solution through iterations. The PSO algorithm first determines some particles at random; each particle has three attributes: position, velocity and fitness. Fitness is an index to measure the quality of particles. The smaller fitness is, the closer to the optimal solution. The calculation error given in Eq. (5) is chosen as the fitness function in this paper. In a multidimensional space, these particles are constantly moving and each particle's fitness is determined by a fitness function that adjusts its speed and direction based on its own experience and that of the population as it moves. In this way, the optimal solution is found gradually in the iterations. The details of PSO are given below:

Suppose there exists a target space with a dimension of d that contains a population of m particles. At the t^{th} iteration, the position of particle i is represented by a vector $X_i(t) = (X_{i1}(t), X_{i2}(t), \ldots, X_{id}(t))$, with a corresponding velocity vector represented by $V_i(t) = (V_{i1}(t), V_{i2}(t), \ldots, V_{id}(t))$. When the PSO algorithm is executed, the position and velocity of the m particles are randomly initialized, and then the optimal solution can be found through iterations. At the t^{th} iteration, particles update their velocity and position by tracking two best values, namely, $\mathbf{P}_{\text{best}}$ (personal best, one best solution obtained by the particle itself), expressed as $P_i(t) = (P_{i1}(t), P_{i2}(t), \ldots, P_{id}(t))$, and $\mathbf{G}_{\text{best}}$ (global best, the best solution found so far by the entire particle swarm), expressed as $P_g(t) = (P_{g1}(t), P_{g2}(t), \ldots, P_{gd}(t))$.

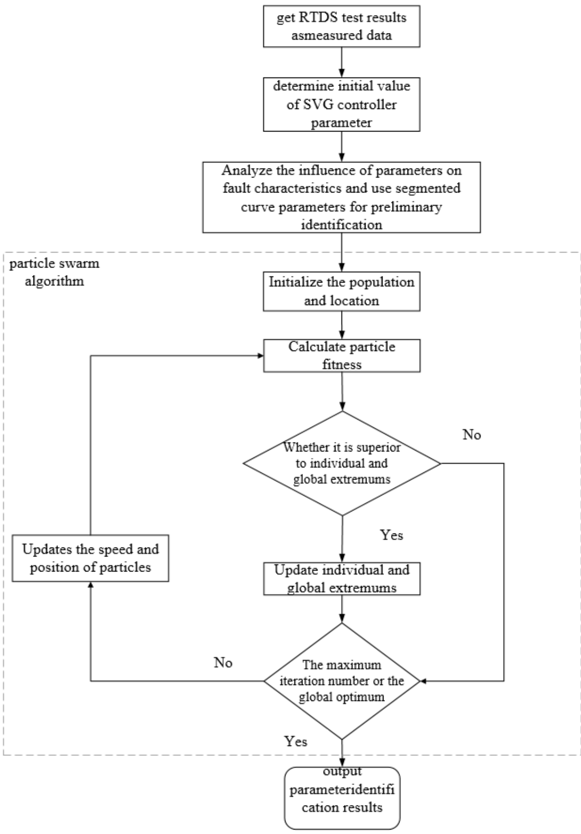


FIGURE 4. Flowchart of the proposed SVG parameter identification method.

At the $(t+1)^{\text{th}}$ iteration, the particle updates its velocity and position by $\mathbf{P}_{\text{best}}$ and $\mathbf{G}_{\text{best}}$ using Eqs. (6) and (7):

$$v_{ik}(t+1) = wv_{ik}(t) + c_1 r_1(p_{ik}(t) - x_{ik}(t)) + c_2 r_2(p_{gk}(t) - x_{ik}(t)) \tag{6}$$

$$x_{ik}(t+1) = x_{ik}(t)) + v_{ik}(t+1) \tag{7}$$

where ω stands for the inertia weight; c_1 and c_2 are learning factors; and r1 and r2 are random numbers generated between (0,1) following the uniform distribution; $i = 1, 2, \ldots, m$, $k = 1, 2, \ldots, d$. V_i is the velocity of the particle in each dimension and V_{max} is the maximum velocity that the particle can reach. After narrowing the parameter range by the grid search method, the number of generation and iteration times of particles are determined. Then, the SVG model parameters with high trajectory sensitivity are precisely identified.

C. MAIN FLOWCHART

The flow chart of the proposed SVG model parameter identification algorithm based on parameter fault characteristics is shown in Figure 4.

VI. CASE STUDIES

A. CALCULATION OF TRAJECTORY SENSITIVITY

Using the trajectory sensitivity calculation method introduced in Section II, the sensitivity values of reactive power, current and voltage for the test system shown in Fig.1 are calculated in Table 3.

TABLE 3. Trajectory sensitivity values of SVG model parameters.

SVG parameters	reactive power sensitivity	current sensitivity	voltage sensitivity
T_1	2.611	1.804	0.003
T_2 (T_4)	3.806	3.802	0.004
T_3 (T_5)	3.684	3.276	0.003
T_p	0.005	0.007	0
T_S	0.811	0.623	0.002
K_P	0.005	0.006	0
K_i	3.009	3.005	0.003
K_d	1.374	1.372	0.001
I_{CMAX}	1.525	1.507	0.015

As can be seen from Table 3, the voltage sensitivity is smaller than the current sensitivity and reactive power sensitivity, so it is not used as a good indicator. Because the current sensitivity values are similar to those of the corresponding reactive power, in this work, only reactive power is chosen as the good indicator to judge the overall sensitivity information. According to the results of trajectory sensitivity calculation, the parameters with high sensitivity are $[T_1, T_2, T_3, T_4, T_5, T_S, K_I, K_D, I_{CMAX}]$, which are selected as candidates for parameter identification.

B. INFLUENCE OF PARAMETERS ON REACTIVE POWER FOR INITIAL IDENTIFICATION

Next, the effect of each parameter on the fault characteristics is explored, which is used to determine those segments of the simulation curves that are more suitable for identifying each SVG model parameter. The corresponding simulation environment is set up in the BPA software, with the one-line diagram given in Fig. 1. A three-phase-to-ground short-circuit fault is applied at bus B1, occurring at 36 cycles and cleared at 86 cycles. One cycle in the simulation is set to 0.02 seconds. The switching reactance is 0.01 H. Reactive power curves at bus B1 are recorded for comparing with the corresponding RTDS measurements.

Fig. 5 provides the simulation results when $T_1 = 0.001$ s and $T_1 = 0.005$s, respectively. From the simulation curves, it can be found that T_1 only affects the starting time of the reactive power drop after fault is cleared. Fig. 6 gives the simulation result comparison when $T_2 = 1$ s and $T_2 = 1.5$ s, respectively. As can been seen from Fig. 6, T_2 mainly affects oscillatory behavior and the final values after swings are settled. Fig. 7 provides the comparison of simulation results when $T_s = 0.003$ s and $T_s = 0.006$ s, respectively. It shows that T_s mainly affects the sudden change and oscillatory behavior of reactive power after fault clearance. Fig. 8 compares the simulation curves of reactive power when $K_i = 300$ and $K_i = 900$, respectively. The simulation

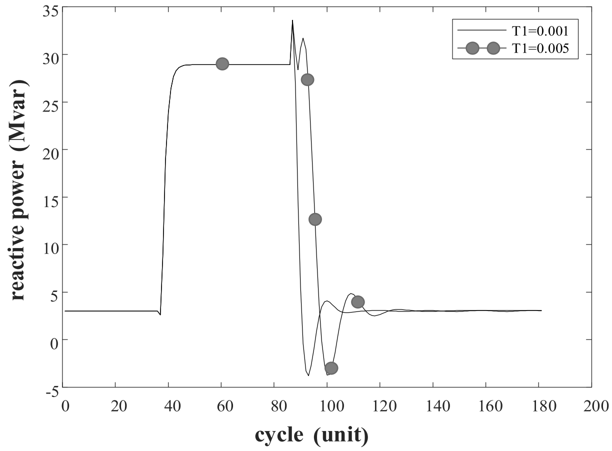


FIGURE 5. The influence of T_1 on the reactive power curve captured at bus B1.

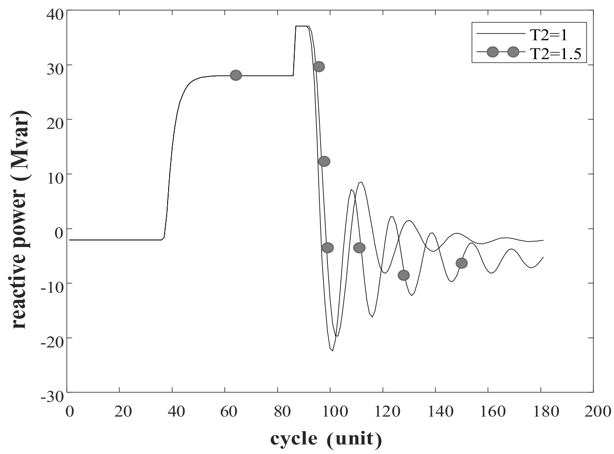


FIGURE 6. The influence of T_2 on the reactive power curve of bus B1.

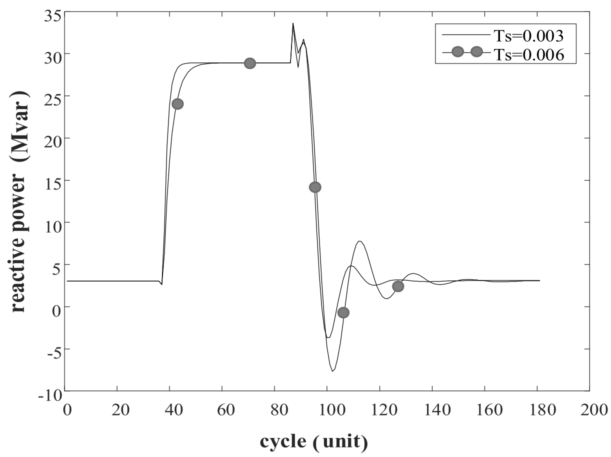


FIGURE 7. The influence of T_S on the reactive power curve at bus B1.

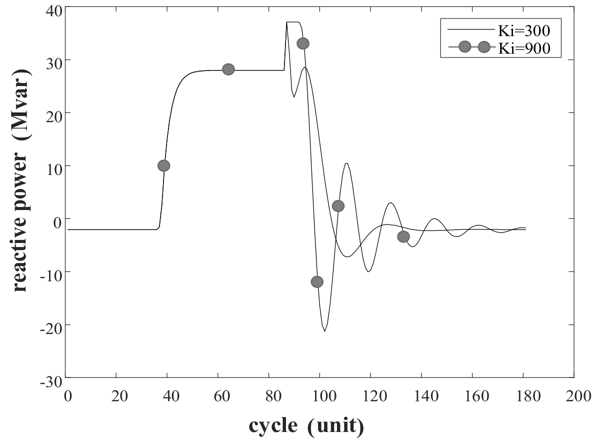


FIGURE 8. The influence of K_i on the reactive power curve at bus B1.

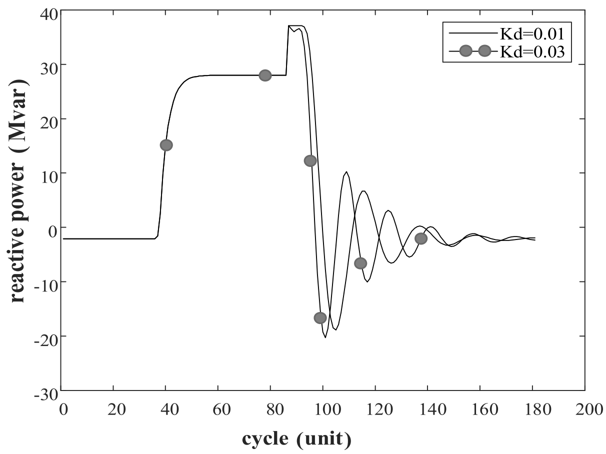


FIGURE 9. The influence of K_d on the reactive power curve at bus B1.

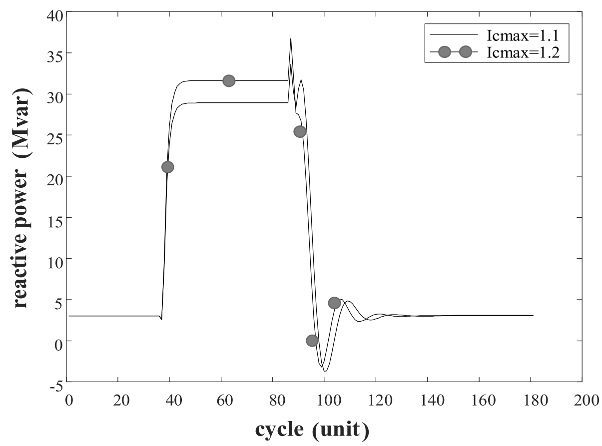


FIGURE 10. The influence of I_{CMAX} on the reactive power curve at bus B1.

results show that K_i also affects the starting time of reactive power drop and the amplitude of oscillation following fault clearance. Fig. 9 provides the comparison of reactive power when $K_d = 0.01$ and $K_d = 0.03$, respectively. T. According to the simulation results, similar to K_i, K_d mainly affects the starting time of reactive power drop and the oscillation amplitude. In Fig. 10, the comparison of reactive power curves is provided, when $I_{CMAX} = 1.1$ and $I_{CMAX} = 1.2$. As can be observed in Fig. 10, I_{CMAX} mainly affects the amplitude of reactive power curve swings during the fault.

TABLE 4. Preliminary results of SVG model parameter identification.

parameter	preliminary identification results
T_1	0.006
T_2	1.00
T_3	1.00
T_4	1.00
T_5	1.00
T_S	0.0058
K_i	800
K_d	0.028
I_{CMAX}	1.2

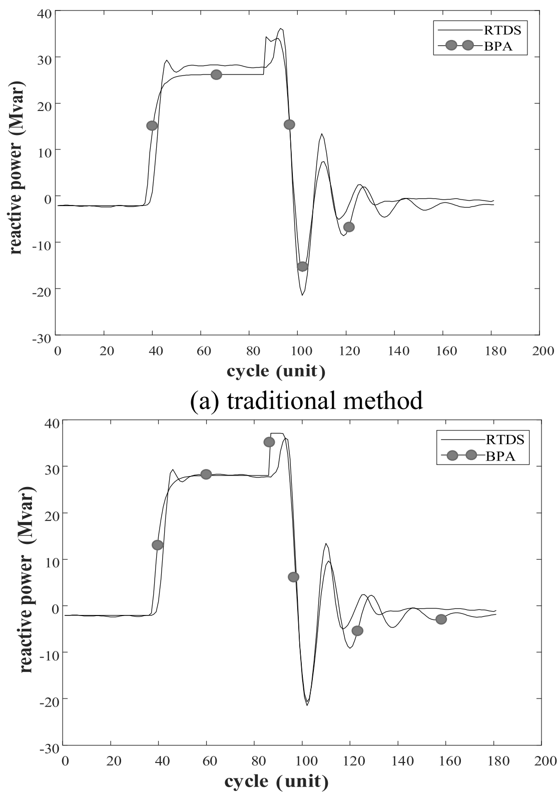


FIGURE 11. Comparison of the reactive power simulation results between the two methods.

The above analysis provides important guidance on the influence of each parameter on different sections of the fault characteristics; the grid search method is used to identify the parameters in different stages, so that the search range of parameters can be greatly reduced. The following strategies are used to achieve this goal:

(1) Determine I_{CMAX} using the reactive power curve during the fault;
(2) Determine T_S using the climbing curve of reactive power when the fault occurs;

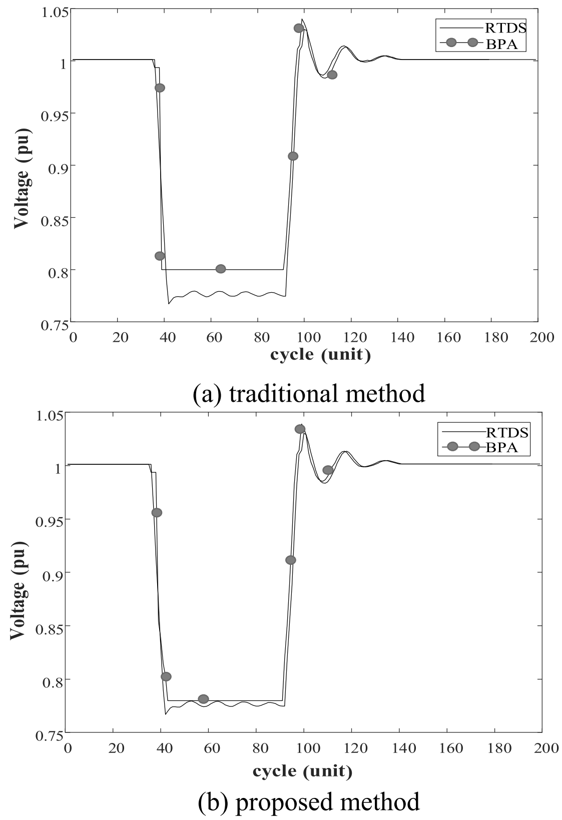


FIGURE 12. Comparison of the voltage simulation results between the two methods.

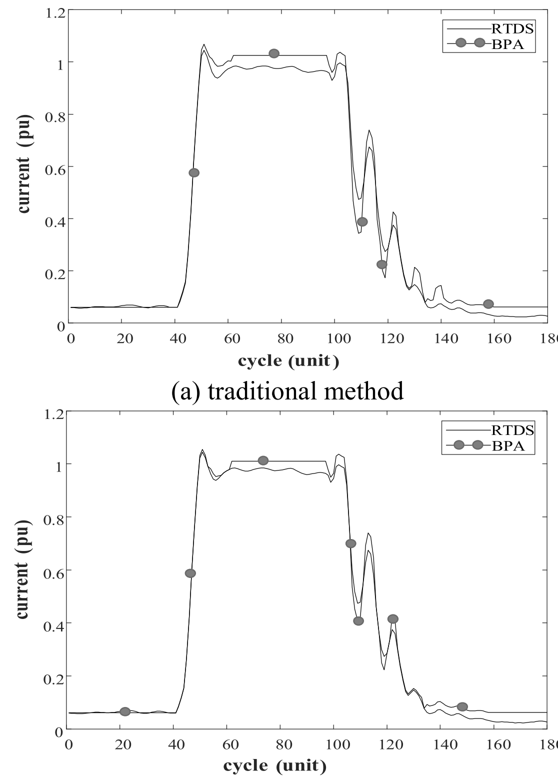
(3) Determine K_i, K_d, T_1 using the section curve when reactive power starts to decline before reaching the minimum value;
(4) Determine T_2, T_3, T_4, T_5 using the oscillatory curve of reactive power.

Using the error calculation method given in Eq.(5) as the fitness value for judging the parameter identification performance, a preliminary set of SVG model parameters can be obtained with the lowest fitting errors, the result of which is given in Table 4.

C. PRECISE IDENTIFICATION OF PARAMETERS

After the initial identification parameters, the search ranges are set from 90% to 110% of their initial values obtained from the above step, in order to the derive the final values of I_{CMAX}, T_s, K_i, K_d, T_1 and T_2. At the "fine" searching stage, the presented PSO algorithm is used by properly setting the number of particles and iteration times, with the objective function given in Eq.(5).

The performance of the proposed method is verified and compared with the traditional particle swarm method, shown in Fig. 11 through Fig. 13 with RTDS representing actual measurements, given in figure (a), and BPA representing simulated curves, given in figure (b). From the reactive power curve, voltage curve as well as current curve at various segments, it can be observed that the simulation results obtained



(a) traditional method

(b) proposed method

FIGURE 13. Comparison of the current simulation results between the two methods.

TABLE 5. Performance comparison between the two methods.

（a）Fitting Errors and Computation Time

	traditional method	proposed method
Time (min)	9.86	6.38
Reactive power error (Mvar)	1514.56	1076.48
Voltage error (pu)	0.62	0.23
Current error (pu)	0.86	0.42

（b）List of Identified Parameters

Parameters	traditional method	Proposed method
T_1	0.0072	0.0063
T_2	1.07	1.006
T_3	1.01	1.002
T_4	1.005	1.003
T_5	1.02	1.002
T_p	0	0
T_S	0.006	0.006
K_P	0.03	0.02
K_i	999	750
K_d	0.023	0.03
V_{MAX}	1	1
V_{MIN}	-1	-1
I_{CMAX}	1.135	1.2
I_{LMAX}	1.1	1.1

using the proposed grid search and PSO-based "coarse-to-fine" searching method are closer to the traditional approach with lower fitting errors. Moreover, the computational speed is faster. Table 5 provides the quantified results of parameter identification errors and computation time, as well as the final estimated parameter sets.

From Table 5(a), the SVG model fitting errors using the identified parameter set with the proposed method are much lower than the traditional method, which verifies the effectiveness of this approach. From Table 5(b), it can be observed that major differences rest with T_1, K_i, K_d, and I_{CMAX}, indicating their importance on SVG model accuracy.

VII. CONCLUSION AND FUTURE WORK

In this paper, a grid searching and PSO based "coarse-to-fine" approach is presented to identify SVG model parameters using segmented measurements. First, the SVG-RTDS testbed is set up to obtain actual measurements, which are compared with results obtained from the BPA transient simulation. To reduce the parameter searching space, trajectory sensitivity analysis is first performed to identify those parameters with higher sensitivities. Then, the effects of various parameters on different segments of the fault curves are studied. The grid searching method is used to provide good preliminary parameter set of SVG, before the PSO algorithm is applied to fine tune the parameter sets in a narrow range, to speed up the entire process. Finally, the effectiveness of the proposed method is verified by comparing the results of traditional parameter identification method with those obtained from the proposed method.

When calculating the sensitivity of SVG model parameters, it perturbs one variable only at a time, while keeping all other parameters constant. However, the nonlinear interaction between different parameters will affect each other in practice. In future work, more research will be conducted to investigate such effects in order to further improve the performance of the proposed method.

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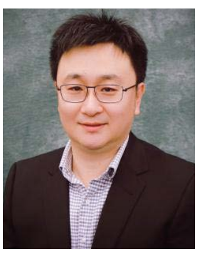

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