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ROBUST PARAMETER DESIGN OF STATIC VAR COMPENSATOR AGAINST PROBABLE DIFFERENT FAULTS

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Abstract

Transient and low-frequency oscillations are primarily caused by disturbances such as faults, load changes, switching operations, etc, in the power system. As modern power systems work on stability margins, fast and successful damping of these oscillations is increasingly challenging. Controllers such as Power System Stabilizers (PSS) and Flexible AC Transmission System (FACTS) devices are widely used to mitigate these oscillations. However, their effectiveness strongly depends on their optimal placement within the network and the correct tuning of their parameters. A major challenge in setting controller gains is that they are usually tuned for a single operating condition. When conditions change, the performance of the controllers may degrade significantly, even leading to unacceptable oscillations. Therefore, it is crucial to design controller parameters that maintain robust performance across a wide range of conditions.

This paper employs a Static VAr Compensator (SVC) to mitigate power system oscillations caused by faults and optimally determines its controller gains to damp oscillations not only for a specific fault but also for various types of faults that may occur. An improved version of the Particle Swarm Optimization (PSO) algorithm is used for solving the optimization problem. The proposed method is applied to a two-machine power system with PSS-equipped generators, and the results are discussed to show the effectiveness of robust determination of SVC controller gains.

1. Introduction

1.1. Motivation

Any delay in suppressing electromechanical oscillations, mainly caused by faults and switching events, may severely compromise system stability and result in cascading failures, as modern power systems often operate close to their stability margins [1]. Static VAr Compensators (SVCs) have a significant role in effectively mitigating these oscillations due to their capabilities in regulating voltage levels and enhancing system damping [2]. However, the performance of such devices is highly dependent on the proper tuning of their controller parameters. Improper coordination of their parameters may reduce the overall damping effectiveness and possibly worsen the system dynamics under certain conditions [3].

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A critical challenge is that controller parameters are often optimized for specific operating conditions or fault scenarios. As a result, when the system faces different disturbances, these controllers may not only fail to mitigate oscillations but might even intensify them, and even lead to system instability. Thus, it is crucial to consider a wide range of operating conditions and fault types when tuning the controller parameters to ensure that the system remains stable under different scenarios. This approach is known as the robust determination of controller parameters [4]. The robust tuning of SVC parameters, particularly when coordinated with Power System Stabilizers (PSSs), becomes even more critical.

This is a large-scale, complex, nonlinear, and non-convex optimization problem, which is difficult to solve using conventional mathematical techniques without introducing major simplifications. Such simplifications often lead to suboptimal solutions. In this context, evolutionary algorithms offer significant advantages over traditional optimization methods. They are completely derivative-free and can be easily applied to any type of objective function with any scale and complexity. Also, their global search capabilities and ability to escape local minima make them particularly suitable for finding the most appropriate solutions [5].

1.2. Literature review

SVCs have been widely studied for enhancing power system stability in the literatures.

Reference [6] reduced LFOs in a power system using an SVC. This approach keeps the system stable and reduces LFOs well during a three-phase fault.

However, some studies focused on load and/ or generation uncertainties in determining SVC controller parameters in single-machine and/ or multi-machine power systems.

Reference [7] took the uncertainty of wind energy into consideration and proposed an adaptive stabilization strategy using an SVC with an additional damping controller structure. Reference [8] reduced oscillations over a wide range of loading conditions with optimal SVC controller parameters using a Bacteria Foraging Optimization (BFO) algorithm. A synergetic controller for the SVC was proposed in a Single-Machine Infinite Bus (SMIB) system with a High Voltage Direct Current (HVDC) link, considering load variations [9]. Considering variations in the operating conditions due to load uncertainty, reference [10] used an SVC to reduce the electromechanical oscillations. Reference [11] proposed a framework for robust stabilization of a single-machine infinite-bus system with an SVC, addressing uncertainties in infinite bus voltage and reactances to the generation station. The approach enhanced both stability and transient performance despite unknown system parameters.

Also, the optimal performance of the SVC in coordination with other power system components, such as other FACTS devices, PSSs, and Automatic Voltage Regulators (AVR), has attracted considerable attention.

A particle swarm optimization (PSO) algorithm was implemented to design the coordinated parameters of the SVC and the Thyristor Controlled Series Capacitor (TCSC) in [12]. Reference [13] used an enhanced intelligent optimization algorithm to optimize the controller parameters of static synchronous compensator (STATCOM), additional power oscillation damping (POD) controller, and PSSs to improve the stability of the power system, including wind turbines and Photo Voltaic (PV) panels. A combined version of the genetic algorithm (GA) and particle swarm algorithm (PSO) was used as an optimization algorithm. To reduce Low-Frequency Oscillatory (LFO) modes arising from the intermittent nature of wind power, loading, and generating conditions, a robust coordinated method was proposed using Particle Swarm Optimization (PSO) for optimizing parameters of controllers of PSS, SVC, and STATCOM [14]. This study tried to optimally find the location and gain parameters for controllers that effectively dampen the LFOs. Reference [15] used a supplementary damping controller for SVC to damp inter-area LFOs, considering the influence of signal transmission delay on damping performance. This study obtained the tradeoff between damping performance and delay margin for the supplementary damping controller. Reference [16] searches for coordinated control actions to different AVR systems and SVC in power systems. The controller parameters of the automatic voltage regulators, power system stabilizers, and SVC were considered in [17] to enhance the electromechanical oscillations.

The SVC has also been considered for various objectives beyond damping oscillations, including voltage regulation, power flow control, and overall system stability enhancement.

Searching for coordinated control actions for different AVR systems and SVC in power systems, reference [16] proposed a predictive control strategy for handling both electromechanical oscillations and voltage drop problems, considering different faults in a multi-objective framework. Reference [18] implements a self-corrective SVC to reduce voltage variations and damp reactive power oscillations after faults in a power system integrated with wind farms and battery storage systems. It uses Grey Wolf Optimizer (GWO) and teaching–learning-based optimization (TLBO) algorithms to solve the optimization problem. Reference [19] simultaneously improved voltage and first-swing stabilities by proposing an integrated approach for their incorporation into the optimal power flow study.

Some recent studies have taken a more integrated view. They consider both load and generation uncertainties. At the same time, they coordinate the SVC with other devices like FACTS, PSSs, and AVRs. These works also aim to achieve several goals together.

Reference [20] improved the voltage stability and the resilience following events with proper control of SVC and STATCOM in the wind turbine integrated power system. The proposed control system aims to control voltage, frequency, and mechanical power under wind/ load variations, faults, and outages.

The controller parameters of the AVR, PSS and SVC were coordinately tuned to enhance the electromechanical and voltage response for several critical operating conditions in [17], using the GA. Two objectives, including damping of electromechanical oscillations and the improvement of the automatic voltage regulator responses, were simultaneously considered. Critical operating conditions included transmission line outages and increasing load demands.

Few studies have addressed the optimal tuning of SVC parameters while considering various types of faults.

Reference [21] damped oscillations using two SVCs with supplementary loops and incorporated the time delay of feedback signals in their controller design to make them robust against uncertainty in the communication latency of feedback signals. This study considers different operating points and faults in evaluating the performance of SVCs. A robust controller to damp out the inter-area oscillations and consequently enhance the stability of the power system was proposed in [22]. The performance of the proposed controller model, including the SVC and the Doubly Fed Induction Generator (DFIG), was tested during different faults. Reference [23] Optimally designed an SVC to improve the dynamic stability of a solar energy-integrated power system. The SVC improves the rotor angle and voltage oscillations because of different disturbances created in the power system. A hybrid optimization approach using PSO and the gravitational search (GS) technique was presented to find optimal SVC damping controller parameters.

1.3. Contribution

The main contribution of this study is the optimal tuning of SVC parameters in a multi-machine PSS-equipped power system to mitigate electromechanical oscillations in power systems under a wide range of fault conditions. Optimizing these parameters based solely on the conventional three-phase fault scenario may lead to suboptimal SVC performance when facing other types of faults. Although this approach may lead to slightly increased oscillations under certain specific fault conditions, it ensures the least overall electromechanical oscillations when the system is exposed to all types of faults.

This study also employs an improved version of the PSO algorithm, which offers greater reliability in finding globally optimal solutions.

1.4. Organization

The remainder of this paper is organized as follows: Section 2 presents the modeling of the SVC and its controller. Section 3 formulates the optimization problem, including the objective function and the system constraints. In Section 4, the proposed solution method is described in detail. Section 5 provides simulation results and analysis, including a case study, modeling assumptions, and a comprehensive discussion of the outcomes. Finally, Section 6 concludes the paper with key findings of the study.

2. SVC and its controller modelling

The SVC can regulate voltage at its terminals by controlling the amount of reactive power injected into or absorbed from the connected bus and enhancing the power grid's stability. The reactive power is adjusted by the firing angle of thyristors, connecting the capacitor and reactor banks to the grid via a coupling transformer. Figure 1 shows a single-line diagram of an SVC and a simplified block diagram of its control system.

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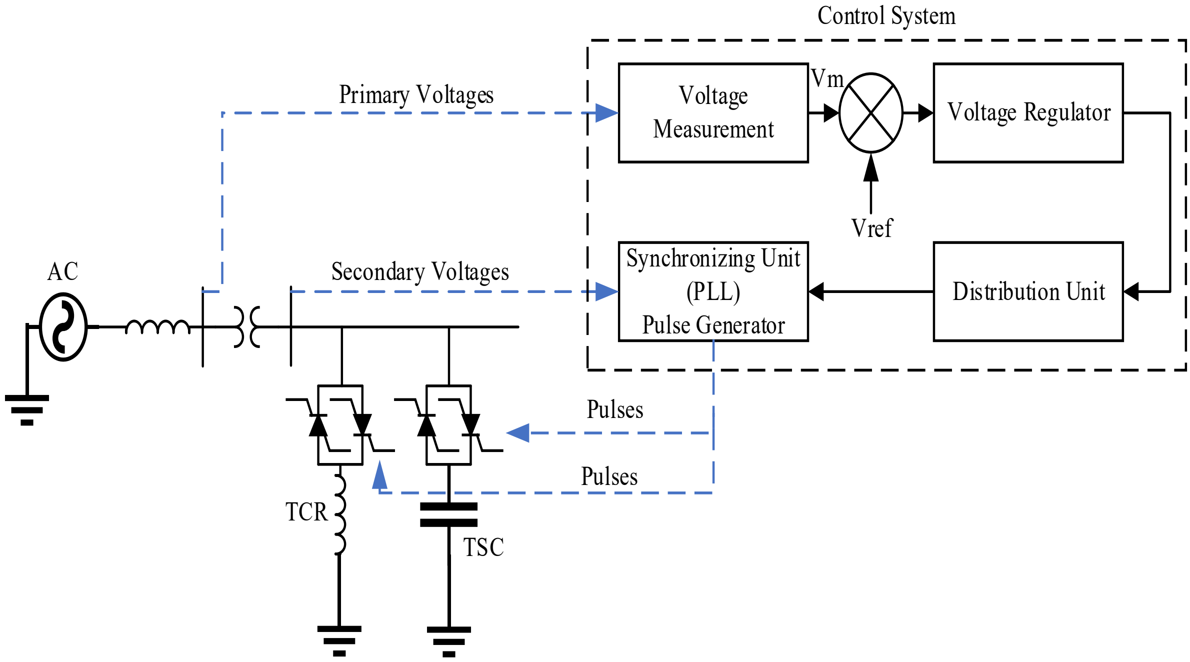

Figure 1: Single-line diagram of an SVC and its control system block diagram.

In the control system indicated by the black dotted-line box, the positive-sequence voltage is first measured. In the voltage regulator, the voltage error, defined as the difference between the measured voltage V_m and the reference voltage V_{ref}, is used to determine the SVC susceptance B required for the voltage to follow V_{ref}. A distribution unit computes the firing angle of the TSC and TCR, and finally, a synchronizing system using a phase-locked loop (PLL) synchronized on the secondary voltages and sends appropriate pulses to the thyristors via a pulse generator.

Figure 2 has a closer look at the voltage regulator. This regulator implements the V-I characteristic to produce the proper values of B in its output. The V-I characteristic is according to Figure 3. The V-I characteristic is described according to (1).

$$V = \begin{cases} V_{ref} + X_s I & B_{cmax} \leq B \leq B_{lmax} \\ \frac{-I}{B_{cmax}} & B \leq B_{cmax} \\ \frac{I}{B_{lmax}} & B_{lmax} \leq B \end{cases} \tag{1}$$

Where;

B, B_{cmax} and B_{lmax} are the SVC susceptance, its inductive limit and capacitive limit, respectively. The SVC susceptance B is limited by the total reactive power of the capacitor banks B_{cmax} and the total reactive power of the reactor banks B_{lmax} and it can't inject or absorb reactive power beyond these limitations.

V and V_{ref} are the SVC terminal voltage and its reference voltage, respectively. The voltage is regulated at the reference voltage V_{ref}.

X_s is the slope or droop reactance as indicated in the V-I characteristic of Figure 3.

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I is the SVC current.

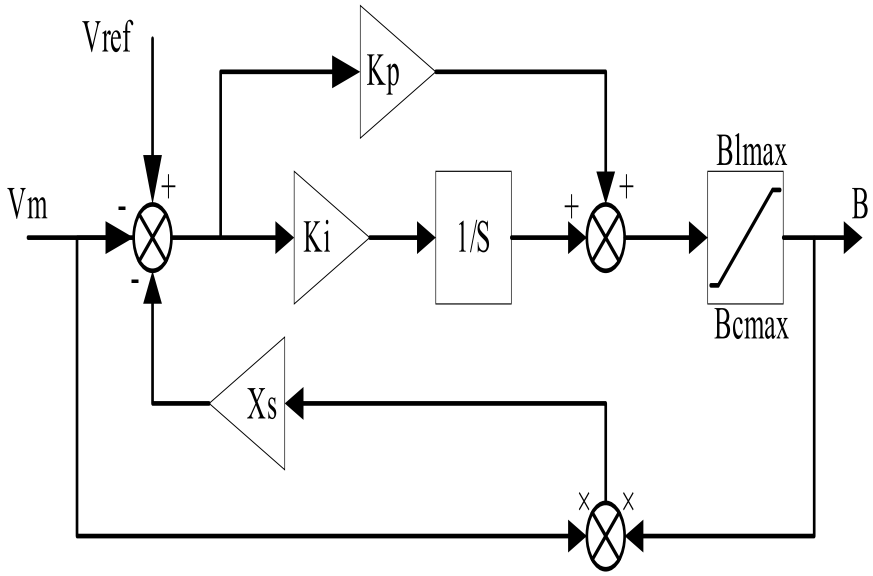

Figure 2: Voltage regulator details.

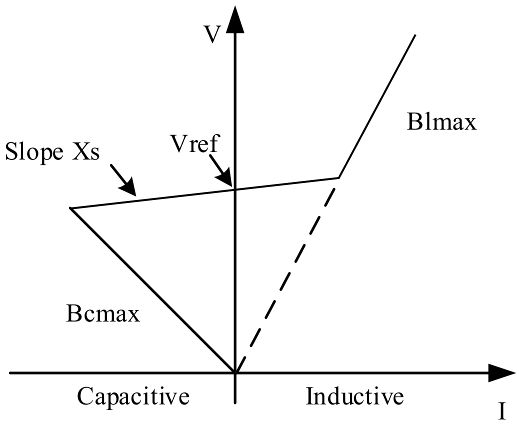

Figure 3: The V-I characteristics of the SVC

The SVC response speed to a change of system voltage depends on the voltage regulator gains (proportional gain K_p and integral gain K_i), the droop reactance X_s.

3. Problem formulation

3.1. Objective function

The objective of this study is to reduce voltage oscillations across all buses and phases following various types of faults. Equation (2) shows the objective function to be minimized.

$$of = \sum_{all\ faults} \sum_{i=1}^{N_{bus}} \sum_{p=a,b,c} \frac{1}{t_{stop} - t_0} \times \int_{t=t_0}^{t_{stop}} \left| V_{i,p}(t) - V_{ref} \right| dt \quad (2)$$

3.2. Constraints

The main constraints are on control variables according to equations (3) to (5).

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$$X_s^{min} \leq X_s \leq X_s^{max} \tag{3}$$

$$K_p^{min} \leq K_p \leq K_p^{max} \tag{4}$$

$$K_i^{min} \leq K_i \leq K_i^{max} \tag{5}$$

4. Solution Method

Due to model simplifications, getting trapped in local optima, and the need for derivatives of often complex objective functions, classic mathematical optimization methods can be inefficient and unreliable when encountering nonconvex and nonlinear multi-dimensional optimization problems. Evolutionary algorithms offer a flexible alternative, working well in high-dimensional and multi-modal spaces. Their population-based approach increases the chance of finding global optima without needing strict problem assumptions.

Kennedy and Eberhart developed the PSO algorithm inspired by the collective foraging behavior of birds. Thanks to its simplicity and few parameters, PSO has been widely used in solving optimization problems. The standard PSO is formulated as equations (6) and (7) [24].

$$V^{k+1} = V^{k+1} + c_1 r_1 (Lbest^k - X^k) + c_2 r_2 (Gbest^k - X^k) \tag{6}$$

$$X^{k+1} = X^k + V^{k+1} \tag{7}$$

Where,

X is the position of the current particles,

V is the velocity vector of particles,

Superscript ^{k} and $^{k+1}$ denote iteration k and K+1, respectively.

c_1 and c_2 are learning factors, which, respectively, represent the cognitive ability and social ability of particles

r_1 and r_2 are uniformly distributed random numbers between 0 to 1.

And $Lbest$ and $Gbest$ is the position of the optimal solution found by the particle itself and the optimal solution found by the whole population at present.

However, this version of the PSO suffers from drawbacks like premature convergence and getting trapped in local optima. To address this, the inertia weight parameter is introduced to better control particle speed and direction. By this technique, expression (6) changes to (8).

$$V^{k+1} = \omega V^{k+1} + c_1 r_1 (Lbest^k - X^k) + c_2 r_2 (Gbest^k - X^k) \tag{8}$$

$$\omega = \frac{iter^{max} - iter}{iter^{max}} \tag{9}$$

In the PSO algorithm, the inertia weight plays a key role in balancing global and local search capabilities. The inertia weight is considered one of the most critical parameters, and many researchers have focused on enhancing it. Two types of inertia weights are commonly used: a fixed weight that maintains consistent particle behavior, and a time-varying weight that dynamically adjusts the particles' search ability throughout the optimization process.

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This study uses a strategy for the inertia weight according to [25]. This inertia factor can be defined as (10) and then can be used in (8).

$$\omega = \frac{1}{1+e^{a-b\times\frac{iter}{iter^{max}}}} \tag{10}$$

This inertia weight gradually increases, allowing for effective local search in the early stages and enhanced global exploration in the later stages. This strategy helps particles escape local optima and leads to better overall solutions. Additionally, each particle retains its best-found position until the end of the process, resulting in multiple near-optimal solutions. The algorithm also shows robustness to population size, maintaining performance even when the number of particles is reduced.

5. Simulation and Results

In this section, the performance of the proposed method is evaluated through simulation studies. The results are analyzed to demonstrate its effectiveness and compare it with existing approaches.

5.1. Case study

Figure 4 shows the single-line diagram of a simple high-voltage, highly loaded 500 kV transmission system used as a case study.

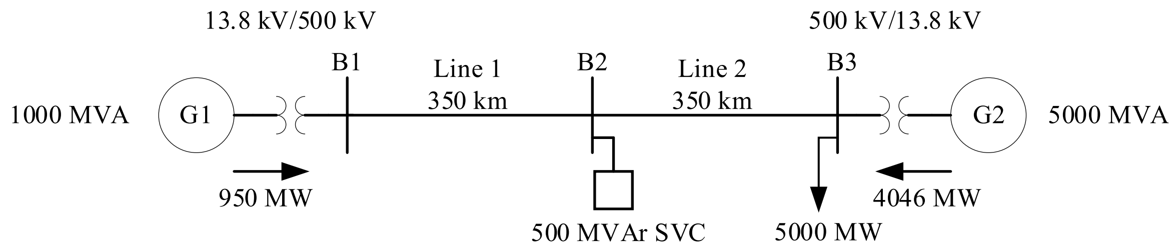

Figure (4):

A 1000 MW hydroelectric power plant (referred to as M1) supplies electricity to a load center via a 500 kV, 700 km transmission line. The load center itself consists of a resistive load rated at 5000 MW. This demand is met by both the distant 1000 MVA hydro plant and a nearby generation facility with a capacity of 5000 MVA (referred to as M2). Based on a load flow analysis, plant M1 is normally generating 950 MW, while the local plant M2 supplies the remaining 4046 MW. The long transmission line delivers 944 MW, nearly matching its surge impedance loading (SIL) of 977 MW. To ensure system stability in the event of faults, a 500 MVAr SVC is installed at the midpoint of the line for shunt compensation. Both generators are equipped with hydraulic turbines and governors (HTG), excitation systems, and power system stabilizers (PSS) to support dynamic performance.

5.2. Assumptions

In order to apply the proposed method to the case study and conduct the optimization algorithm some assumptions are made as follows.

Faults occur at 0.1 sec after starting the simulation and are cleared after 4 cycles, 0.08 sec. with a fault clearance time of 0.18 sec.

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The fault location is on bus #01,

Fault types include three-phase short circuit, single-phase to ground, two-phase and two-phase to ground,

The SVC three-phase base power is 500 MVA, and its reactive power limit is ±500 MVAr,

${X_s}^{min}$ and ${X_s}^{max}$ in equation (3) are 0.005 and 0.1, respectively,

${K_p}^{min}$ and ${K_p}^{max}$ in equation (4) are 0.1 and 500, respectively,

${K_i}^{min}$ and ${K_i}^{max}$ in equation (5) are 1 and 1000, respectively,

Related to the PSO optimization algorithm, the number of particles is 9, the number of iterations is 1000, the cognitive parameter is 1, and the social parameter is 3.

a and b in the equation (10) are 2 and 0.5, respectively.

5.3. Results and discussions

Table 1 presents the obtained solutions for two cases: in the first case, only a 3-phase short circuit is considered, and in the second case, all fault types are considered. These two solutions are quantitatively compared in Table 2, in which the value of the objective function, expression (2), is presented. As seen, in the conventional method, considering only a 3-phase short circuit, the value of expression (2) is 0.1050, while this value is increased to 0.1921 in the proposed robust method. This shows that the oscillations in the proposed robust scheme get worse! But it presents better values for other types of faults. After a 1-phase to ground fault, the value of expression (2) in the conventional method is 0.1561, and this is bigger than the value of the objective function in the proposed robust scheme, i.e., 0.1498. This shows that Oscillations after a 1-phase to ground short circuit in the proposed robust scheme are damped faster compared to the conventional method.

Also, noting the faults 2-phase and 2-phase to ground in table 2, oscillations in the proposed robust scheme are damped faster compared to the conventional method.

Table 1: Solutions obtained by two conventional and robust scheme

	Conventional method	Proposed method (Robust Scheme)
X_s	0.0891	0.0285
K_p	254.6101	17.2460
K_i	914.5745	371.7669

Table 2: oscillations criteria as expression (2) for different types of faults by two conventional and robust scheme

	Conventional method	Proposed method (Robust Scheme)

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3 phase	0.1050	0.1921
1 phase to ground	0.1561	0.1498
2 phase	0.1703	0.1484
2 phase to ground	0.1925	0.1780

Figures (5) to (8) compare the mentioned oscillations to give a better understanding of two solutions encountering different types of faults. In these figures, the vertical axis is limited to 0.3 to 1.2 to show the oscillations with more detail.

Figure (5) shows the oscillations arising after clearing a 3-phase short circuit. As seen in this figure, the conventional method is more successful in damping oscillations compared to the proposed robust technique. Also, the final value of the voltage is closer to 1 p.u. The reason is that the proposed method tries to improve the oscillations in all types of faults and not only in the 3-phase short circuit case. This result is achieved only at the cost of moving away from the optimal solution in the 3-phase short circuit. However, it is expected that other types of faults get damped faster in the proposed robust scheme.

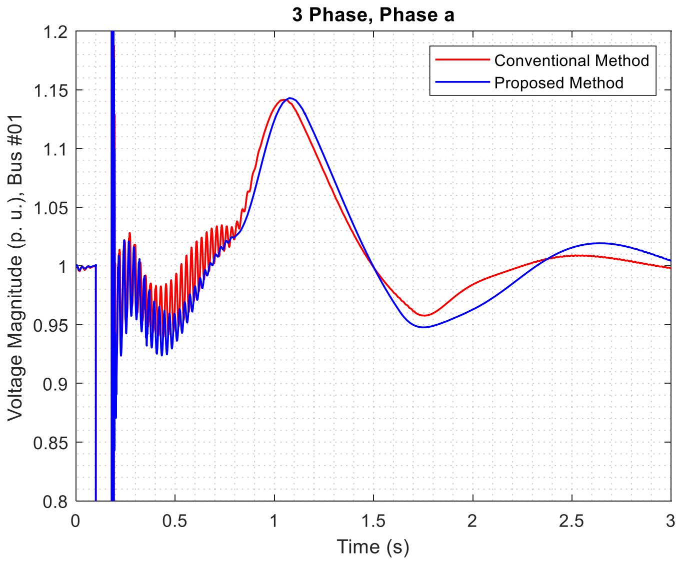

Figure (5): Bus #01, phase a voltage magnitude oscillation after a three phase short circuit by two conventional and proposed methods

Figure (6) shows the performance of two conventional and robust techniques in damping oscillations after clearing a 1-phase to ground fault in 0.18 sec. As seen, the proposed method is considerably more successful, 6. Please note that only phase a of bus 01 is presented, and there are the same conclusions for other phases and other buses.

Figure (7), shows the performance of two conventional and robust techniques in damping oscillations after clearing a 2-phase fault in 0.18 sec. The proposed method damps the oscillations more successfully. There is the same conclusion for damping oscillations after a 2 phase to ground fault as shown in figure (8).

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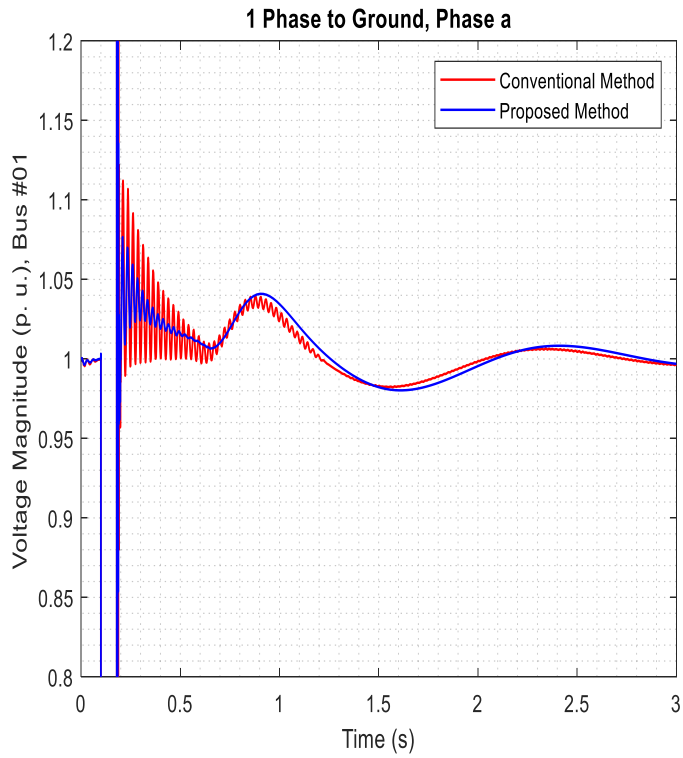

Figure (6): Bus #01, phase a voltage magnitude oscillation after a single phase to ground short circuit by two conventional and proposed methods

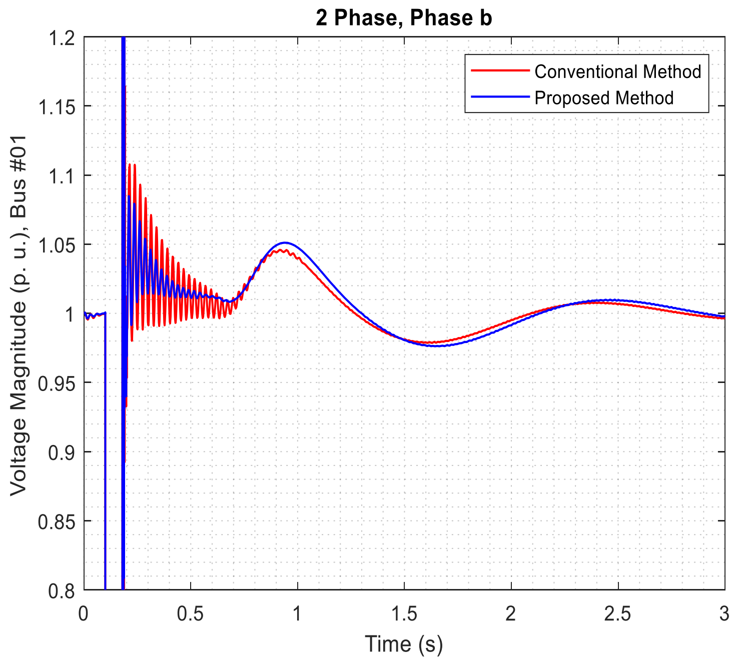

Figure (7): Bus #01, phase b voltage magnitude oscillation after a two phase short circuit by two conventional and proposed methods

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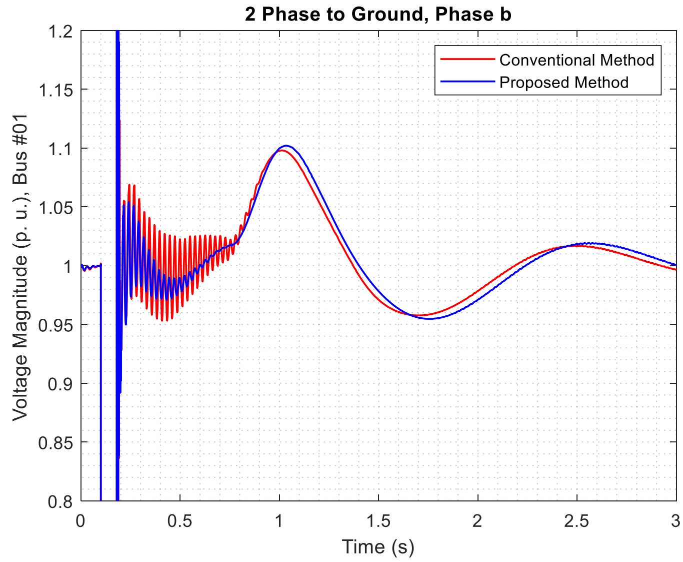

Figure (8): Bus #01, phase b voltage magnitude oscillation after a two phase to ground short circuit by two conventional and proposed methods

6. Conclusion

Power systems face a range of disturbances, not just one. This paper tackled the challenge of damping power system oscillations under various fault conditions. An SVC with optimally tuned controller gains, utilizing an improved PSO algorithm, was proposed. A robust tuning approach helps maintain stability across all these situations. It's more flexible, more practical, and better suited for real-world grids.

While conventional methods for tuning SVC controller gains may offer optimal performance under a specific disturbance, such as a three-phase short circuit, they often fail to provide acceptable responses under other fault scenarios. The proposed robust method may be slightly less effective in that one case, but it significantly improves damping for other fault types of disturbances, such as single-phase-to-ground, two-phase, and two-phase-to-ground faults.

Therefore, the proposed robust tuning method offers a more reliable and adaptable solution for practical power systems, where operating conditions and fault types are inherently variable. It ensures system stability not only under a fixed fault scenario but across a broad range of disturbances, making it a promising approach for enhancing the resiliency of the modern power grid

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