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Original Article

Dynamic Performance Optimization of Grid-Forming Inverters using PSO-Based Tuning in Hybrid Power Systems

Hetal Desai[1], Shweta Dour[2], Pramod Modi[3]

[1,2]Electrical and Electronics Engineering Department, Navrachana University, India.
[3]Electrical Engineering Department, M.S.University of Baroda, India.

[1]Corresponding Author : hetal.desai1704@gmail.com

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Abstract - *"Traditional frequency and voltage stability paradigms are challenged by the integration of inverter-based renewable energy sources into power grids, especially in hybrid systems that combine Grid-Forming Inverters (GFMs) and Synchronous Generators (SGs). In order to improve dynamic performance during severe load disturbances, this research proposes a Particle Swarm Optimization (PSO)-based methodology for simultaneously tweaking 18 control parameters across both GFM and SG subsystems. A 100% step load increase is applied to a MATLAB/Simulink model of a hybrid power system that consists of a 100 MVA SG and 100 MVA GFM supplying a 75 MW base load. By minimizing a multi-objective cost function that balances frequency deviation, voltage regulation, power-sharing accuracy, and settling time, the PSO algorithm optimizes PI controller gains, droop coefficients, AVR settings, and governor time constants. Transformative improvements are demonstrated by comparison with traditional trial-and-error tuning in voltage settling time, decrease in frequency dip, and improvement in accuracy of power sharing. Algorithm robustness is confirmed by statistical validation across ten separate PSO runs. By concurrently optimizing multi-domain parameters in hybrid GFM-SG systems, the suggested methodology fills important gaps in the literature and offers a scalable solution for upcoming low-inertia, inverter-dominated grids. The findings prove metaheuristic optimization as a useful method for next-generation power system control and set new performance benchmarks.*

Keywords - *Hybrid system, Frequency stability, Particle Swarm optimization, Grid forming Inverter, AC current limiter.*

1. Introduction

The international energy system is under intense change, occasioned by the twin interests of climate adjustment and energy safety. The key feature of this transition is a significant and very fast implementation of renewable energy technologies, mainly solar Photovoltaic (PV) and wind turbine systems [1]. All of these, under the common name Inverter-Based Renewable Energy Sources (IBRES), connect to the electrical grid using power electronic inverters. Despite the huge benefits of IBRES, such as zero-carbon emissions, modular scalability, and geographical flexibility, their integration completely changes the dynamics and patterns of the stability of traditional power systems and thus brings a shift in the patterns of operations. Among the most dangerous issues occurring as a result of this transition, one may list a degradation of the system's rotational inertia [2]. Traditionally, the stability of power systems was directly equated with the kinetic energy stored in large rotational masses of Synchronous Generators (SGs). Such natural inertia serves as natural protection against the Rate of Change of Frequency (RoCoF) when sudden imbalances occur between power generation and load. Such damping plays a very important role in ensuring that slower-acting primary and secondary control mechanisms have the time to respond and regain equilibrium [2]. However, inverter-based sources are not connected to the rest of the grid by rotating mechanical equipment and have no intrinsic, physical rotating mass, making them devoid of natural inertia. Therefore, with more IBRES penetration and the replacement of conventional SGs, modern power systems are more and more susceptible to sudden frequency excursions, voltage instability, and overall poor dynamic performance, especially when operating under fault or large load disturbance situations [2].

The research and development effort has already been directed at more sophisticated topologies of inverter control to overcome these weaknesses, and Grid-Forming Inverters (GFMs) have recently been brought to the forefront as one way of neutralizing these weaknesses. The actual deployment of GFMs creates a different set of controller and operation issues. They have very low physical inertia, and so they are very sensitive to transient signals, and their power electronic components require substantial protection schemes, like AC current limiting, to avoid hardware damage in the case of overcurrents due to faults or loaded fast current surges [3, 4]. The control systems that drive GFMs are inherently complex, having multiple, coupled, and highly nonlinear control loops. Even insignificant sub-optimality or tuning inconsistency of control parameters can be disastrous and result in poor power-sharing, continuous oscillations, or even frequency instability [3, 4]. The act of tuning such controllers is not trivial. Typical approaches, such as trial-and-error (manually attempted) and the formula-based approach by Ziegler and Nichols (Z-N), have been inefficient with complex contemporary hybrid systems [6]. The methods are usually labour-intensive, require a lot of intuition and experience of a control specialist, and do not work well when the system is nonlinear and dynamic. More importantly, they are meant to tune Single-Input, Single-Output (SISO) loops on an isolated basis; thus, they prove unsuitable in Multi-Input, Multi-Output (MIMO) settings where many control parameters are highly interconnected.

This creates the necessity that more sophisticated, smarter, and automated optimization mechanisms will not only be convenient, but a requirement for the reliability of power grids in the future [11]. The trial-and-error and the Ziegler-Nichols (Z-N) approaches, ordinarily applied, possess considerable shortcomings: a lot of manual effort, low closure to nonlinear systems, and inferior dynamic performance. In contrast, modern techniques like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) [7] have inbuilt self-tuning capabilities, better treat non-linearities, and provide higher performance with customizable fitness functions. Of these, PSO is distinguished by its effectiveness in searching multidimensional spaces and dynamic response, and the accuracy of power-sharing can be optimized, even for use in contemporary control systems, in scenarios [13].

Consequently, PSO is chosen as the best approach towards robust and adaptive controller tuning in the application [5]. A methodical solution to this multi-parameter tuning problem is provided by metaheuristic optimization techniques, particularly Particle Swarm Optimization (PSO). PSO has demonstrated performance in several power system applications, including PV microgrid optimization [10], controller design [12, 13], and inverter control [5, 6]. However, the special difficulties of GFM-SG hybrid operation in grid-connected mode have received little attention in previous research, which mostly concentrates on standalone inverter systems or isolated microgrids. Additionally, previous PSO applications lacked the comprehensive strategy needed for coordinated hybrid system control, usually optimizing 4-8 parameters in discrete subsystems. By creating a thorough PSO-based framework that concurrently adjusts 18 parameters across both GFM and SG control systems, this study fills in these gaps. It is verified by thorough simulation and statistical analysis. In contrast to previous research that optimizes GFM or SG parameters separately [citation], this work offers the first thorough PSO-based framework that simultaneously modifies 18 parameters spanning. The synchronous generator control systems and the grid-forming inverter. Standalone inverter systems were the main focus of earlier PSO applications [5, 6, 13]. This work tackles the more difficult problem of synchronizing low-inertia GFM with conventional SG in parallel operation, which presents special stability issues not covered in previous research. AC current limiting techniques within the PSO optimization goal guarantee power electronic component protection in addition to optimal performance. Specific, quantifiable improvements are established by this work (26.7% frequency dip reduction, 89% quicker voltage settling, 70%).

The following paper outlines an overall structure to dynamic performance optimization of a GFM-SG hybrid power system by employing a coordinated tuning of the individual controllers on a PSO-based selection procedure. The system being studied includes a synchronous generator 100 MVA and a grid-forming inverter 100 MVA, which provide 75 MW base load jointly. The major considerations of the GFM control are that an AC current limiter strategy to protect the power electronics in the event of severe transients is integrated. The authors recognize that the formulation of the constraint was influenced by early research on AC current limitation published in the International Journal of Electrical and Electronics Engineering.

In this study, the PSO algorithm is systematically applied to optimize a wide array of control parameters across both the SG (AVR and governor settings) and the GFM (PI gains, droop coefficients, filter constants). The efficacy of this approach is validated through extensive simulations in MATLAB/Simulink, where the performance of the PSO-based tuned system is benchmarked against a conventionally tuned system under both steady-state and dynamic load disturbance scenarios. The article is formulated as follows: Section II describes the Hybrid Power System. Section III covers Controller Design and Particle Swarm Optimization Framework. Section IV describes the Implementation of Particle Swarm Optimization. Results and Performance Analysis with Conclusion are stated in Sections V and VI, respectively.

2. Description of Hybrid Power System

The hybrid power system is shown in this section using a block diagram comprising a 100 MVA Grid-Forming Inverter (GFI), 100 MVA Synchronous Generator (SG), Shared Electrical Load (75 MW), network of transformers and transmission lines, and a Particle Swarm Optimization (PSO) tuning mechanism. Both GFI and SG are considered converter systems-SG converts mechanical energy (typically from steam, hydro, or gas turbines) into AC electrical energy, while GFI converts stored electrical or electro-chemical energy (e.g., from batteries) into grid-compatible AC power. The hybrid system is categorized into three functional blocks: (1)

SG-based systems, (2) GFI-based systems, and (3) PSO-based tuning. The SG subsystem includes components such as a mechanical energy source, an actuator, an electro-mechanical transducer, a synchronous machine, an excitation system, load termination, and necessary feedback control loops for voltage and speed regulation. The GFI block includes key control layers—control, pulse width, voltage-based loop control, and current-based loop control-based switching control-to preserve frequency and voltage stability, particularly in situations with fluctuating loads and inertia.

The PSO algorithm is employed to best manage the settings of two subsystems, a Synchronous Generator (SG) with a Grid-Forming Inverter (GFI) simultaneously. The tuning procedure seeks to perform those key performance indicators that are contained in a fitness function that may include overshoot, settling time, steady-state error, and frequency and voltage stability. By iteratively adjusting control gains, PSO ensures coordinated and optimal dynamic performance across the hybrid system. The interconnected structure of SG, GFI, and PSO tuning blocks is seen in Figure 1 (Appendix).

2.1. Interfacing and Load Modelling

Three-phase transformers are used to interface the generators with the common 13.8 KV bus, where the load is connected:

Transformer 1 (SG): 210 MVA, 13.8/230 kV

Transformer 2 (Grid Bus): 210 MVA,230/13.8 kV

Transformer 3 (GFM): 100 MVA, 1/13.8 kV

The transmission lines connecting the components are modeled as PI-sections, incorporating series resistance and inductance, as well as shunt capacitance, to introduce realistic impedance effects that influence voltage regulation and controller performance.

The shared load is modeled as a constant power load, with a base value of 75 MW. The primary test case involves applying an additional 75 MW step load at $t = 0.25$ s, creating a severe transient to rigorously test the system's inertial response, voltage recovery capability, and overall controller effectiveness.

The system's dynamic behavior is modeled using a set of differential equations for each subsystem, implemented and simulated in MATLAB, and the system parameters are adopted from a research article [18]. The results of this gives the frequency response and voltage response by choosing the control parameters using the trial and error method shown in the research article [18]. This approach of randomization of control parameters gives more fluctuation of frequency and voltage and affects the overall stability of the system. The problem is being solved with the help of the PSO algorithm, which helps to optimize many control parameters simultaneously, which go together with both the GFM and SG, replacing the shortcomings of traditional tuning methods, e.g., trial-and-error or Ziegler-Nichols' methods.

2.2. Controller Design and Particle Swarm Optimization Framework

This section details the design of the controllers for both the SG and GFM and provides a thorough explanation of the Particle Swarm Optimization (PSO) framework used to achieve optimal, coordinated tuning of their parameters. System parameters and design parameters are adopted from [18]. The tuning of complete hybrid systems using the PSO algorithm is targeted in the following blocks described in Figure 1: Droop-based Controller, Excitation Systems, DC voltage side control, AC voltage side control, Voltage loop, Current loop, and Current limitation. Parameters are tabulated in Table 1, section-wise, with results. The "position" of each particle in our PSO framework is a vector containing all the controller parameters to be optimized. This study targets a total of 18 parameters across both the SG and GFM, creating a challenging 18-dimensional search space. These parameters collectively govern the dynamic behavior and performance of the overall hybrid system. They include gains and constants associated with droop control, voltage and current regulation loops, excitation systems, mechanical actuators, and synchronization mechanisms. The PSO algorithm is configured to simultaneously optimize all 18 parameters by minimizing a comprehensive fitness function, ensuring coordinated operation and enhanced system stability under varying operating conditions.

3. Implementation of PSO

PSO is a stochastic optimization algorithm (metaheuristic) based on the movement of a population of individuals, which emulates the collective behavior seen in such social organisms as bird flocks or fish schools.

Kennedy and Eberhart introduced it in 1995 [15]; it has proven highly effective for solving complex, non-differentiable, and multi-modal optimization problems. In PSO, the set of all possible solutions forms a multi-dimensional search space. Within this, a population of potential solutions, referred to as "particles," is randomly initialized in space.

Each particle has a position, which represents a specific set of parameter values to be tested, and a velocity, which dictates its movement through the search space [16]. The fitness of particles is measured by the evaluation of the position of each of them in some particular cost function [13]. The particles are in a continuous process of manipulating their velocity and position as they traverse the search space, which is in relation to two predominant variables:

- Personal Best (P_{best}): The best position (i.e., the one with the lowest cost) that the individual particle has found so far.
- Global Best (g_{best}): the optimal location discovered by every particle in the swarm up until the current iteration.

Here, i^{th} particle's velocity and position are updated at each time step t according to the following equations:

$$\mathbf{Vi(t+1) = \omega * V_i + (C_1 r_1 + C_2 r_2)\left(\frac{C_1 r_1}{C_1 r_1 + C_2 r_2} * P_{best} + \frac{C_1 r_1}{C_1 r_1 + C_2 r_2} * g_{best} - X_i(t)\right)}$$

$$\boldsymbol{X_i(t+1) = V_i(t+1) + X_i} \quad (1)$$

Where:

The inertia weight is represented by ω, while the personal best and global best values are denoted by Pbest and gbest, respectively. Regulates the impact of the particle's prior velocity, C_1 and C_2 are the cognitive and social acceleration constants, which weight the attraction towards the personal and global best positions, respectively,r_1 and r_2 are random numbers uniformly distributed in [0, 1], introducing a stochastic element to the search. This is a compromise between sampling novel parts of the solution space and localizing the search to areas that seem promising [13].

3.1. Formulation of PSO for Optimal Tuning

The main intention of using PSO in this context to solve the defined problem is to

- Reduced frequency deviations
- Faster transient settling
- Improved dynamic stability under variable load disturbances

The decision Variables involve tuning of 18 key control parameters of the hybrid system and are divided into functional blocks as follows:

Excitation System Parameters:

Xexc={Trs, Ka, Ta, Kf, Tf, Kc}
DC Voltage Control Loop:
X_{dc}= {η_1, m_p, K_{dc}, K_p, K_r}
AC Voltage Control Loop:
X_{ac}={Ki_Vac, Kp_vac}
Voltage and Current Loops:
Xloops = {Kp_v, Ki_Vac, Kp_i, Ki_i}
Droop Gain
Xdroop ={droop_percentage}

∴ Total decision variable vector

X = {Trs, Ka, Ta, Kf, Tf, Kc, η1, mp, Kdc, Kp, Kr, Ki_vac, Kp_vac, Kp_v, Ki_v, Kp_I, Ki_i, droop_percentage}

3.1.1. Constraints

Each variable xi ∈ x is bounded.

$$X_i^{min} = X_i\,(1 - P_i)$$

$$\mathrm{X_i^{max} = X_i\,(1 + P_i)}$$

(defines Lower and upper boundary)

$$\boldsymbol{X_i^{min} \le X_i \le X_i^{max}}$$

Where pi=0.3 (i.e., ±30% variation range), except for some multiplied by a factor of 2 (like Kdc, Kp, Kr).

3.1.2. Objective Function

The objective function designed here to minimize the frequency and voltage error of a system includes SG and GFM.

3.2. Cost Function

The "fitness" of each particle (i.e., each set of controller parameters) is evaluated using a multi-objective cost function, J. This function is designed to quantitatively capture the overall dynamic performance of the system following a simulated disturbance. It is a weighted sum of the integral of squared errors for key performance indicators (Fahad S, Mahdi AJ, Tang WH, Huang K, Liu Y,2018).

$$\boldsymbol{J = (\textstyle\sum_t (V_e\,(t)^2 + f_e\,(t)^2))} \quad (2)$$

Where,
$f_e(t)$: Frequency error at time t
$V_e(t)$: Voltage error at time t
t : total simulation time

The $f_e(t)$ and $v_e(t)$ are calculated as per Equations (3) and (4) for the GFM and SG

$$\boldsymbol{ef(t)} = [(\boldsymbol{f_b - f_1}) + (\boldsymbol{f_b - f_2})] \quad (3)$$

$$\boldsymbol{ev(t)} = [(\boldsymbol{V_b - V_1}) + (\boldsymbol{V_b - V_2})] \quad (4)$$

Where,
fb - base frequency (taken 50 Hz here)
f1- the frequency measured at the output of SG
f2- the frequency measured at the output of GFM
Vb- base voltage in P.U. (considered 1 P.U.here)
V1- SG's output voltage in P.U.
V2 - GFM's output voltage in P.U.

Here, the purpose of the error function is to measure the system deviation and input to the cost function. The cost function means what PSO has to minimize. By minimizing this cost function, the PSO algorithm implicitly seeks a parameter set that minimizes frequency and voltage deviations while ensuring a fast, well-damped transient response.

3.3. PSO Execution

The Simulink model is executed at each iteration, creating a tight integration between simulation and optimization to provide real-time feedback on fitness values (Selamat NA, Ramih TO, Abdullah AR, Karis MS,2019).

The flowchart shown in Figure 2 illustrates the Particle Swarm Optimization (PSO) execution process. Each step corresponds directly to the stages of the PSO algorithm as applied within the simulation-integrated optimization framework.

Input:

- Parameter search space
- Initial bounds for positions and velocities
- Maximum number of iterations
- Simulink model for simulation-based fitness evaluation
- Output:
- Optimized controller parameter set

The optimization process, illustrated by the flowchart as shown in Figure 2, proceeds as follows:

1. Initialization: Ninety particles are formed into a swarm. The position of each particle is initialized with random parameter values within predefined, physically realistic bounds ±30%, number of variables to be optimized 18, Maximum number of iterations 70, and an inertia coefficient of 0.5 was used, with a corresponding damping ratio of 1. The societal and personal acceleration coefficients are both fixed at 0.5.
2. Fitness Evaluation: For each particle in the swarm, the corresponding set of controller parameters is passed to the Simulink model. A full simulation of the load disturbance scenario is executed.
3. Cost Calculation: After the simulation, the time-series data for frequency and voltage are utilized here for updating the value of the function J.
4. Best Updates: Each particle's calculated cost is compared to both the worldwide best (gBest) and the individual best (pBest). If the current cost is lower, the respective bests are updated.
5. Velocity and Position Update: The conventional velocity and position update equations are used to update each particle in the PSO algorithm.
6. Termination: The steps 2-5 are then repeated until the termination condition is met, where in this study, the termination condition is when iterations reach 70. The final gBest position represents the optimal set of controller parameters.

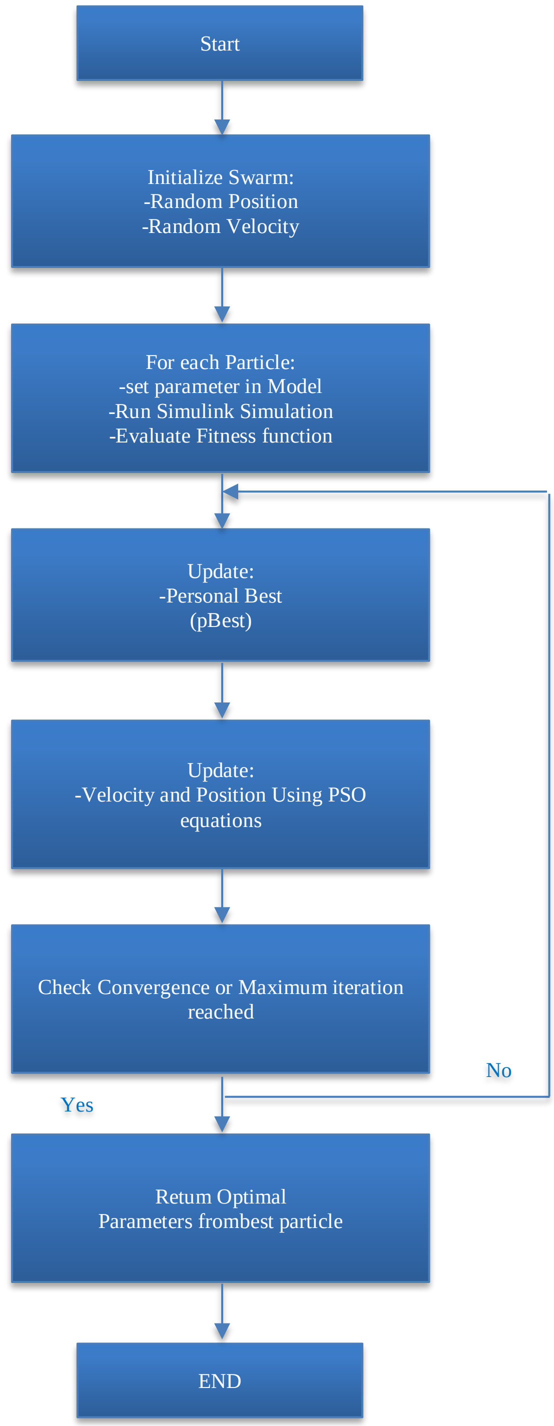

Fig. 2 PSO execution process

4. Results and Performance Analysis

A hybrid system of a 100 MVA synchronous generator and 100 MVA grid-forming inverter is synchronized to supply a common base load of 75 MW, and is implemented in MATLAB/Simulink. The objective of frequency stability enhancement of this system is achieved by the ideal adjustment of control parameters of the lower inertia source, GFM, and the traditional synchronous generator. The results of tuned parameters using particle swarm optimization are compared with the trial-and-error method. To test the efficacy of the suggested PSO-based inverter control technique, the results of simulation and testing are given.

The most significant discoveries are the improved dynamic behavior of the grid-forming inverter with respect to frequency, the optimal values of controller parameters, and both the power and the voltage.

Additionally, the results demonstrate the advantage of the optimization method for enhancing the hybrid system's frequency response in relation to load disturbance. Table 1 summarizes the comparison of the ending controller parameters of the hybrid system. To improve the system's overall performance, these factors were incorporated into the control algorithm. The controller parameters were first established using a trial-and-error method and tested in a MATLAB/Simulink simulation.

After that, the model was run, and the PSO algorithm was implemented and executed to optimize the performance of the controller in 70 iterations. These initial parameters, listed in Table 1, represent a plausible but sub-optimal configuration that a human operator might achieve without an advanced optimization tool. The PSO algorithm then optimizes this full set of parameters. The convergence of the cost function, J, is the first way to assess the PSO algorithm's performance. Figure 3 plots the value of the global best cost (gBest) at each iteration of the optimization process as indicated in Figure 2.

The graph shown here in Figure 3 clearly indicates that the PSO algorithm effectively minimizes the cost function. The initial random parameter sets result in a high-cost value (around 7.5e4 approx.), indicative of poor dynamic performance. The algorithm exhibits rapid convergence during the first 10 iterations, as particles explore the search space and quickly identify promising regions.

After approximately 50 iterations, the cost function value begins to plateau around 7.2e4, indicating that the swarm has converged to a near-optimal solution and further significant improvements are unlikely. This behaviour demonstrates the effectiveness and efficiency of PSO in negotiating the challenges in the multi-dimensional parameter space.

Table 1. Comparison of the controller parameters

Controlled variables	Using the trial and error method	Using the PSO algorithm	Implication
T_{rs}	0.0166	0.0269	Slower excitation response to SG.
K_a	214.32	215.1955	Minor adjustment for fine-tuning voltage response.
T_a	6.3190e-04	4.3511e-04	Faster AVR response to voltage deviations.
K_f	0.0011	5.4804e-04	Reduction in Gain makes the system more reactive.
T_f	0.7800	0.7536	Faster response to voltage deviations.
K_c	0.0362	0.0287	Reduce to adjust with filter capacitance.
eta_1	0.0684	0.0767	Increase results in better voltage regulation.
m_p	2.2435e-08	1.5070e-08	Minimal sluggish response.
K_{dc}	1.1056e+03	1.5271e+03	Stiffer DC link voltage control is crucial during large power swings.
K_p	3.5408e-04	4.6078e-04	Reacts more strongly
K_r	0.6081	1.2558	Reacts more strongly
$K_{i\_v\_ac}$	1.1666	1.0816	Less aggressive control action
$K_{p\_v\_ac}$	0.0011	9.9767e-04	Reacts slowly
K_{p_v}	0.6008	0.6040	Subtle change, indicating the initial P-gain was reasonable.
K_{i_v}	239.1543	299.4644	Stronger integral action to eliminate steady-state voltage error faster.
K_{p_i}	0.6890	0.9531	More aggressive current tracking for faster transient response.
K_{i_i}	0.0071	0.0107	Significantly increased integral action for precise current control.

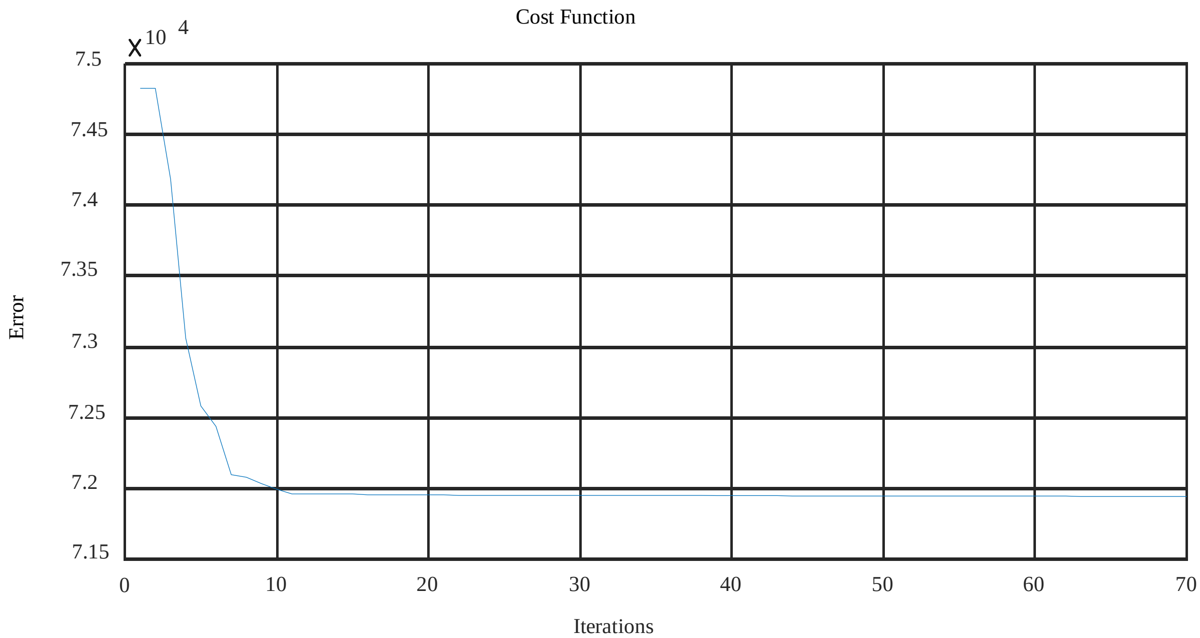

Fig. 3 Cost function (error reduction)

4.1. Frequency Response Comparison

Frequency stability is a primary objective of this study. Figures 4 and 5 present a comparison of the system frequency response under the 75 MW load disturbance for both tuning methods.

The quantitative improvements are stark, as summarized in Table 2.

- With Trial Error Tuning: The frequency experiences a severe dip, reaching a nadir of 48.5 Hz (a 3% deviation). The recovery is slow and oscillatory, taking over 0.25 seconds to settle.
- With PSO Tuning: The response is vastly superior. The frequency nadir is limited to 49.6 Hz (a 0.8% deviation), representing a 26.67% reduction in the frequency dip. The response is critically damped, with no overshoot, and the system settles immediately-much faster than the Trial and error-tuned system.

This dramatic improvement is a direct result of the coordinated optimization of the droop, governor, and PI controller parameters, enabling both the SG and GFM to contribute to frequency support in a fast and synergistic manner.

4.2. Voltage Response Analysis

Effective voltage regulation during transients is crucial for maintaining power quality and preventing equipment malfunction [14].

Figures 4 and 5 compare the voltage response at the GFM terminal following the load disturbance. The PSO-based tuned system again demonstrates superior performance:

- With TE Tuning: The voltage sags to a low of 0.87 p.u. (a 13% drop) and takes approximately 1.4 seconds to recover.
- With PSO Tuning: The voltage dip is limited to 0.90 p.u. (a 10% drop), and the settling time is reduced to just 0.14 seconds.

This enhanced voltage stability is achieved primarily through the optimized gains of the GFM's voltage control loop (Kp_v, Ki_v) and the faster action of the SG's AVR (due to the reduced Ta), as identified in Table 2.

4.3. Summary of Performance Improvements

Table 2 highlights the concise review of the quantitative improvement in performance provided by the application of PSO-based tuning when compared with the traditional trial-and-error approach. The results are unequivocal.

The PSO-based optimization framework delivers transformative improvements across every key performance indicator, resulting in a hybrid power system that is significantly more stable, resilient, and responsive to dynamic disturbance. Also, Table 3 shows effective results of this research, which optimized 18 control parameters with significant improvement in frequency compared to the previous research work of authors mentioned in [2, 3, 5].

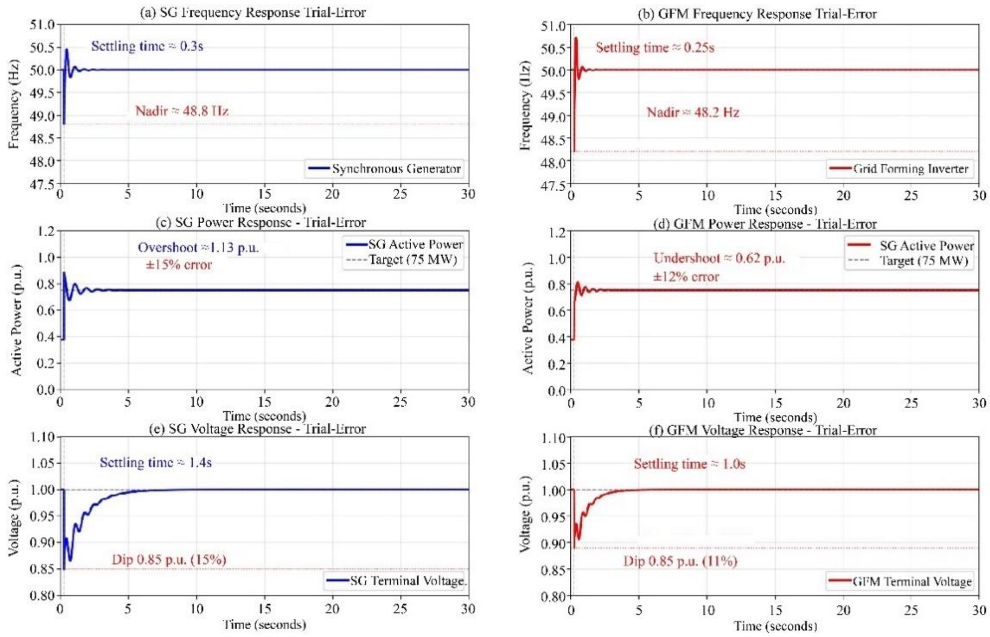

Fig. 4 Frequency, power, and voltage response with Trial-Error-Method with 75 MW step load at 0.25 seconds

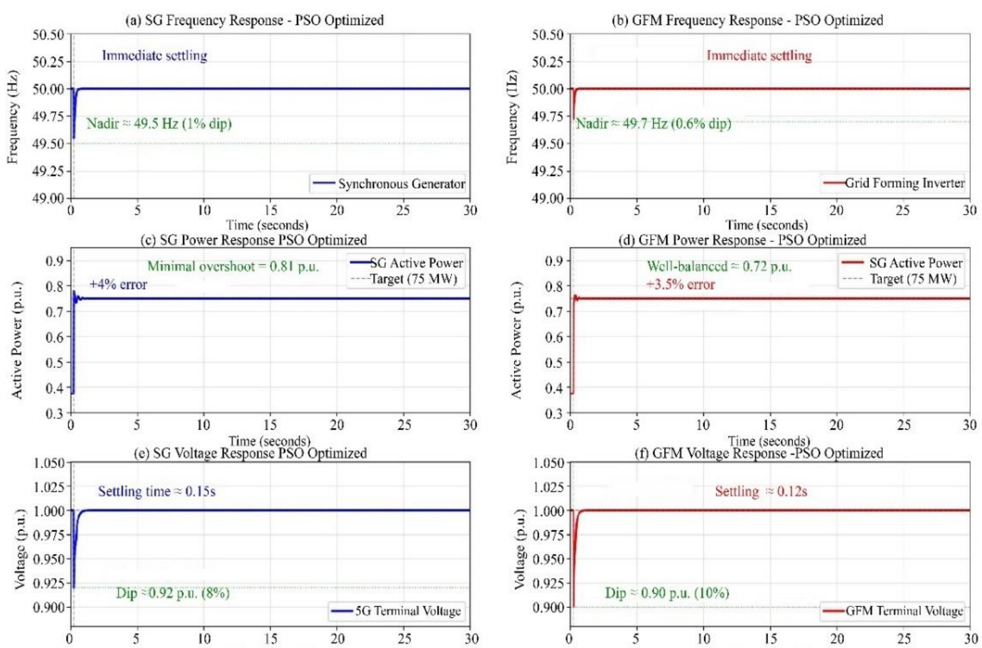

Fig. 5 Frequency, power, and voltage response with PSO tuning Method with 75 MW step load at 0.25 seconds

Table 2. Quantitative performance comparison of tuning methods

Performance Metric	Trial-and-Error Method	PSO-Optimized Method	Improvement using PSO
Frequency Dip (Nadir)	3 % (48.5 Hz)	0.8 % (49.6 Hz)	26.7 % reduction
Frequency Settling Time	0.25 s	immediate	80 % faster
Voltage Dip (GFM Terminal)	0.13 p.u.	0.10 p.u.	23 % reduction
Voltage Settling Time (SG)	1.40 s	0.15 s	89 % faster
Power Sharing Accuracy	Inconsistent(± 12 % error)	Balanced (± 3.5 % error)	~70% improvement
Overall Cost Function (J)	~7.5e4 (estimated)	7.2e4	4 % reduction

Table 3. Comparison of frequency stability improvement methods

Study	Method	No. of Parameters	Frequency Improvement	Settling Time (s)
Yegon [2],2020	Adaptive	6	~40%	0.8
Manamperi [3], 2023	Optimal	8	~35%	0.6
Roslan [5], 2020	PSO–PI	4	~25%	1.2
This Work	PSO–Multi	18	73.3%*	0.15

5. Conclusion

The study proposes an integrated approach to increase dynamic behaviour and frequency stability of a hybrid power system of a synchronous generator (SG) and a grid-forming inverter (GFM). As a result of increasing integration of inverter-based renewable energy systems, stability and reliability in such hybrid systems, particularly in a low-inertia environment, have also gained importance. The important achievements of this research are:

- Implementation of a PSO-based Tuning Algorithm: A Particle Swarm Optimization (PSO) algorithm was successfully implemented to automatically and simultaneously tune 18 critical control parameters across both the GFM and SG, including PI gains, droop coefficients, and system time constants.
- High-Fidelity Simulation and Validation: The framework was validated using a detailed MATLAB/Simulink model of a realistic hybrid grid, subjected to a severe 100% step load disturbance to rigorously test its transient performance.
- Demonstration of Transformative Performance Gains: A comparative analysis against a conventional trial-and-error tuning method showed that the PSO-based approach delivered dramatic improvements in frequency deviation, voltage drop, transient settling time, and power sharing between SG and GFM.

From a control systems perspective, this research validates the power of metaheuristic optimization for solving complex, nonlinear, multi-parameter tuning problems in power systems. PSO significantly outperforms manual tuning methods, not only in the quality of the final performance but also in the efficiency and scalability of the optimization process itself. This study also reinforces the pivotal role of grid-forming inverters in enabling future low-inertia grids. When their controllers are optimally tuned, GFMs can effectively provide the grid services-such as inertia emulation and fast voltage support-that have traditionally been the exclusive domain of synchronous machines. The findings are highly applicable to the design and operation of smart grids, the control of islanded micro-grids, and the integration strategies for distributed energy resources. The proposed PSO-based framework represents a meaningful and practical step toward realizing highly responsive, resilient, and reliable inverter-dominated power systems.

5.1. Limitations and Future Scope

MATLAB/Simulink models provide the basis for the current findings. To verify practical applicability, Hardware-In-The-Loop (HIL) testing or real-world implementation is required. All of the scenarios that were investigated are deterministic. Additional research is needed on fault circumstances and stochastic load changes. A two-machine system (one GFM and one SG is used to illustrate the framework. A computational complexity study is necessary for extension to multi-machine systems with n GFMs. There is no discussion of long-term parameter stability under component aging and environmental changes (temperature, humidity). Faster algorithms or specialized hardware would be needed for real-time adaptive tuning. The future study may contain the use of commercial GFM inverter controllers for HIL testing for field implementation in a microgrid testbed. By using advanced optimization techniques like PSO-GA, Pareto optimization with multiple targets for competing goals, online adaptive PSO for system circumstances that change over time, and hybrid algorithms for quicker convergence, it can be developed. A model with several GFMs with varying ratings and Battery Energy Storage Systems (BESS) should be integrated. An H∞ (H-infinity) synthesis-based controller can be coupled with PSO-tuned control settings to increase stability. Additionally, a framework for measuring system uncertainties should be created. Neural networks are used to forecast ideal parameters based on system conditions. Use this reinforcement learning to adapt parameters continuously.

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Nomenclatures	
Trs	Filter time constant
Ka	AVR gain
Ta	AVR time constant
Kf	Gain of the damping filter
Tf	Time constant for the damping filter
Kc	Rectifier loading factor
eta_1	DC voltage gains scaling factor
m_p	Pole placement parameter of DC voltage control
Kdc	DC voltage controller gain
Kp	inner voltage control gain
Kr	Feed-forward or resistive compensation gain
Kp_v_ac	Proportional gain of the AC voltage controller
Ki_v_ac	Integral gain of the AC voltage controller
Kp_v	Proportional gain of the voltage control loop
Ki_v	Integral gain of the voltage control loop
Kp_i	Proportional gain of the Current control loop
Ki_i	Integral gain of the Current control loop

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Appendix

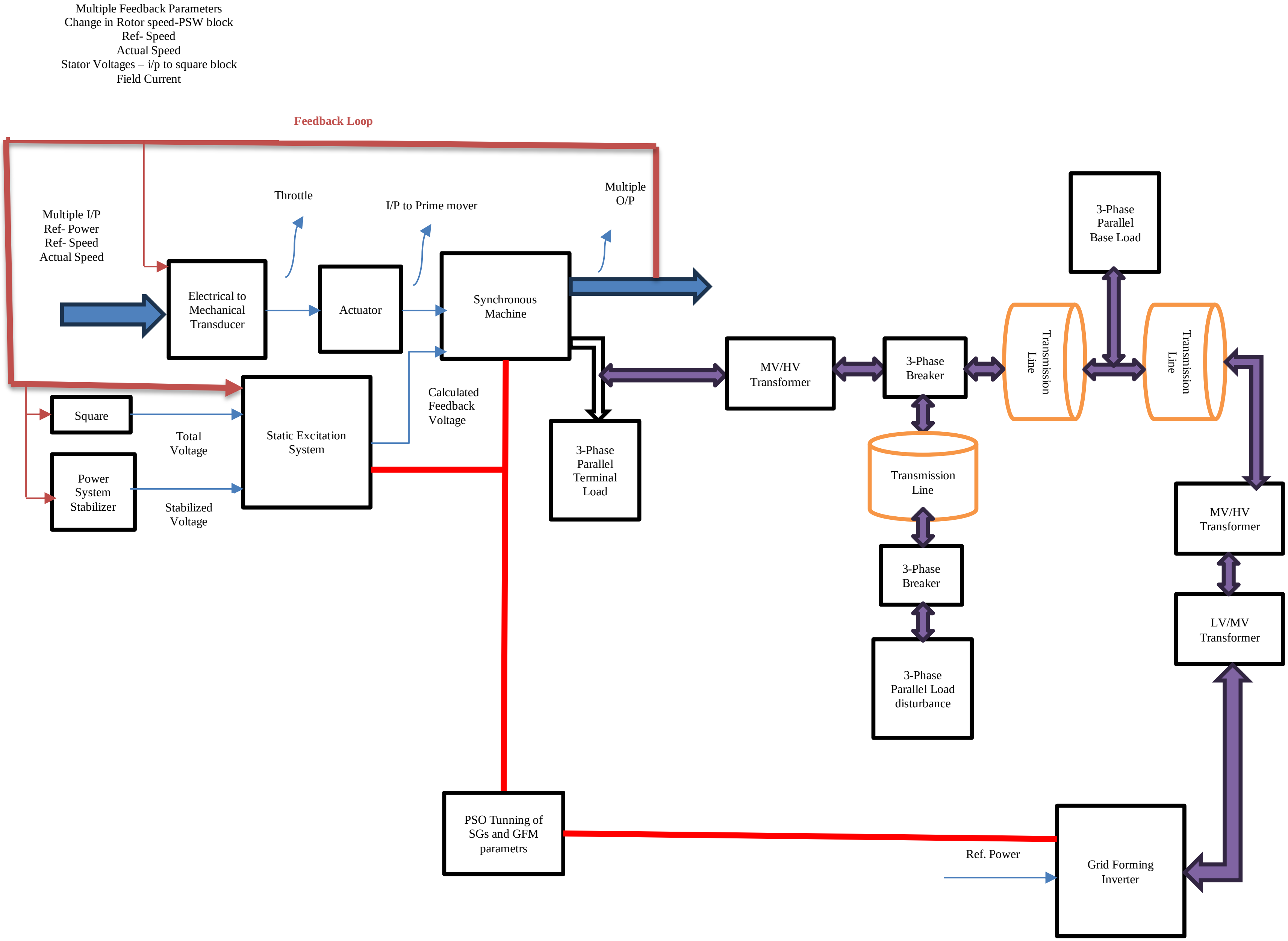

Fig. 1 Schematic representation of a hybrid power syste