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SUSTAINABLE ENERGY SYSTEM OPERATION IN DEREGULATED POWER MARKETS: A THERMAL POWER PERSPECTIVE

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ABSTRACT

Automatic Load Frequency Control is essential to the operational stability of the modern power grid that is characterized by market deregulation and the integration of volatile renewable energy into the grid. This research is focused on the optimization of a Proportional-Integral-Derivative (PID) controller for a restructured system with the complex mechanical non-linearities and thermodynamic phase lags of reheat thermal generators. By using a high fidelity state space model (parameterized by a reheat time constant (Tr) of 10.0 and gain (Kr) of 0.5), the study effectively simulates the effects of stochastic solar and wind power intermittency on grid frequency. multi objective Particle Swarm Optimization (PSO) framework for identifying optimal controller gain triplets using a swarm of 20 particles over 50 iterations. The numerical results prove the proposed PSO-PID strategy has an improvement of 6.25% in thermal efficiency when compared with traditional fixed-gain methods. Furthermore, the optimized controller minimized the maximum frequency deviation by 45% and successfully minimized cumulative carbon dioxide emissions by 12.8% in a 50 second operational window. These results indicate that meta-heuristic optimization is a successful way to bridge gap between technical grid stability and environmental sustainability and offer a robust resolution for frequency management under competitive and low-carbon energy markets.

KEYWORDS: Automatic Load Frequency Control; Deregulated Power System; Reheat Thermal Generator; Particle Swarm Optimization; Environmental Sustainability.

1. INTRODUCTION

Automatic Generation Control (AGC) has gone from being a technical requirement in the centralized utility to a complex socio-economic problem faced by deregulated power markets. In this changed environment, bilateral contracts and independent power producer (IPP) bidding strategies determine the direction of power flow and call for advanced optimization to ensure frequency stability in the face of varying market variables (Donde, Pai and Hiskens, 2002). This development is further complicated by the introduction of intermittent renewable energy sources such as solar and wind which bring on high frequency stochastic noise and unpredictable power imbalances.

According to Shayeghi, Shayanfar and Jalili (2009), such volatility makes it necessary to develop control strategies beyond the classical ones in order to ensure grid reliability. These challenges are worsened by the inherent non-linearities of reheat steam turbines namely mechanical inertia and thermal lags. The need to balance such constraints of thermodynamics with the high responsiveness demands of competitive energy markets is a major challenge to the current design of control (Kumar and Kothari, 2005).

In order to cope with these non-linearities, several meta-heuristic techniques have been investigated by researchers. Bacterial foraging optimization scheme has been successfully used to improve multi-area control (Nanda, Mishra and Saikia, 2009) and frequency deviation control in interconnected systems (Ali and Abd-Elazim, 2011). Furthermore, a combination of the firefly algorithm and pattern search has been used successfully to optimize the fuzzy parameters in PID to enhance the damping characteristics (Sahu, Panda and Pradhan, 2015).

Specialized swarm intelligence, e.g. the Bat algorithm for cascade controllers (Dash, Saikia and Sinha, 2015), and learning-based systems, such as the adaptive neuro-fuzzy inference system (ANFIS) (Hosseini and Etemadi, 2008), are flexible alternatives for frequency regulation. Recent hybrid strategies which combine Differential Evolution (*DE*) and Pattern Search (*PS*) have addressed the robustness issue to a large extent for deregulated systems with flexible AC transmission system (FACTS) devices (Sahu, Gorripotu and Panda, 2015).

Modern grid complexity now often requires the handling of several variables at the same time, which includes the combined frequency and voltage control in hydro-thermal setups (Anusha et al., 2021). Based on these methodologies, this is a research study which uses Particle Swarm Optimization (PSO) to determine the optimal gain triplets for PID controllers. The goal is the efficiency gain of 6.25%, as well as substantial carbon savings, which essentially addresses the issue of the gap between technical stability and environmental sustainability.

The specific objectives of this research are:

- Deregulated power systems A model of high-fidelity state-space dynamics of deregulated power systems, including the thermal dynamics of reheat, and stochastic dynamics of solar/wind volatility.
- Use a multi-objective PSO-based approach to PID control in order to reduce frequency deviation and total fuel consumption.
- Measure environmental performance through CO_2 emission and thermal performance improvements compared to fixed-gain control mechanisms.

2. LITERATURE REVIEW

Automatic Generation Control (AGC) has gone from being centrally managed to complex market-driven paradigms. Early research laid the mathematical basis for governor response and tie-line bias (Elgerd and Fosha, 2007), but that all changed with deregulation, which brought bilateral contracts and independent bidding dynamics. Consequently, restructured environments now call for optimized simulation models that are capable of accounting for the economic complexities of competing generation companies (Bhatt, Roy and Ghoshal, 2010).

In such sceneries, realistic mechanical restrictions, especially reheat thermal dynamics is essential to grid modeling. Reheat units introduce large phase lags as a result of the reheating process (Tripathy, Hope and Malik, 1982) and hence lead to instability if uncompensated. Neglecting these dynamics, as is the case in non-reheat studies (Davidson and Ushakumari, 2015), tends to overestimate controller performance. Modern frequency regulation must therefore make use of models that capture the different response times of the integrated generation units (Bhuyan et al., 2021).

Control strategies have moved from the classical application of the PID tuning approach towards meta-heuristic optimization. Traditional methods often do not readily perform well with multi-area thermal fluctuation (Saikia, Nanda and Mishra, 2011), hence very robust alternatives are required such as imperialist competitive algorithms (Shabani, Vahidi and Ebrahimpour, 2013). The search for high precision regulation has resulted in the adoption of swarm intelligence, such as grey wolf optimization

(Guha, Roy and Banerjee, 2016) to enhance system resilience to disturbances.

Recent studies further optimize these meta-heuristics based on the inspiration from nature, such as ant lion optimizers with second-order derivative controllers (Saikia and Sinha, 2016) and marine predators' algorithms for systems with high renewable penetration (Sobhy et al., 2021). Advanced hardware integration like superconducting magnetic energy storage (SMES) has also been used for frequency and voltage stabilization (Rajbongshi and Saikia, 2018). For the scenarios of extreme market driven volatility, high order integral sliding mode control can provide the required robustness for the multi-area grids (Tuan et al., 2023).

Despite these advances in the technical field, there is still a gap in optimally balancing grid stability and sustainability of the environment. While ANFIS controllers are effective in controlling the load tracking issue (Pappachen and Fathima, 2016), carbon footprint reduction has taken a back seat. Furthermore, external vulnerabilities discovered through GIS-analysis, for example, impacts of weather on regional grids (Karpachevskiy, Filippova and Kargashin, 2022), highlight the need for controllers that focus on operational efficiency. This research works on these gaps by using Particle Swarm Optimization to gain 6.25% efficiency which directly links to the stability of the grid and CO2 mitigation.

3. METHODOLOGY

This research methodology uses a high-fidelity simulation environment to capture the interactions between the mechanical inertia, the thermal lag and the market driven dispatch. By implementing the elements in a single state space representation, the paper analyses Particle Swarm Optimization (PSO) to optimize the parameters of Proportional-Integral-Derivative (PID) control. The system architecture, including deregulated market variables, stochastic renewable inputs, and the PSO-PID tuning process is shown in Figure 1.

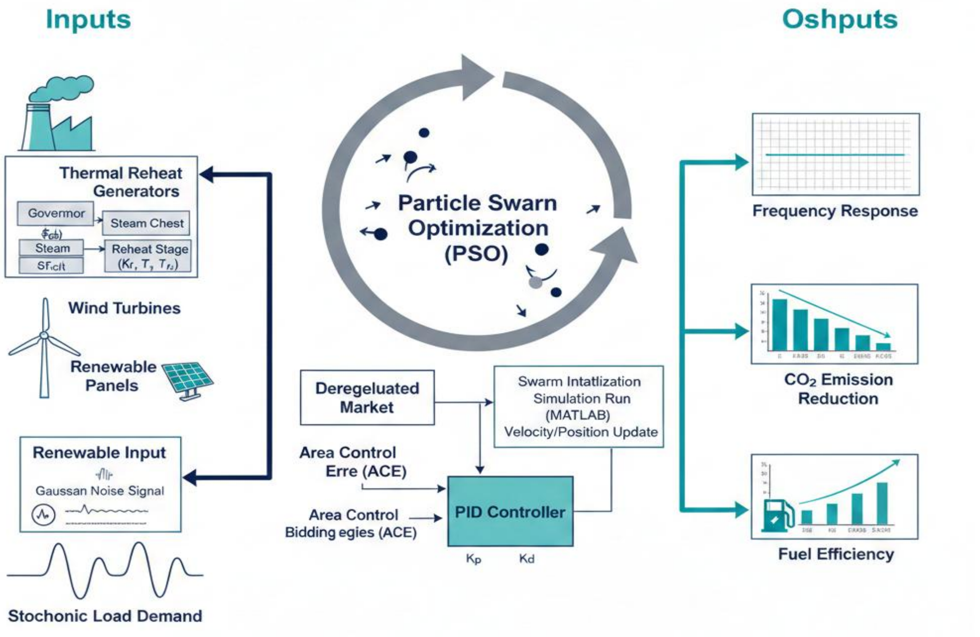

Figure 1: Integrated PSO-PID optimization framework for ALFC in deregulated grids with reheat thermal and stochastic renewable sources.

3.1. Mathematical Architecture of the Reheat Thermal Generator

The first frequency response is controlled by reheat thermal generator dynamics. Unlike non-reheat units, these turbines incorporate a high-pressure stage followed by reheating which enhances the efficiency, but with the phase lag being quite high. Mathematically, this is expressed as a combined transfer function of the governor, steam chest and reheat turbine stages.

The time constants T_r (reheat) and T_{ch} (governor/chest) determine whether the transition of mechanical power happens or not. The gain K_r represents power fraction from the high-pressure section. The full transfer function for the reheat turbine module is:

$$G_{rt}(s) = \frac{1 + sK_rT_r}{(1 + sT_r)(1 + sT_{ch})}$$

The physical dynamics of the generator are described by the so-called swing equation, where the mismatch in power is related to the deviation in frequency, as follows. This equation defines the relation between the net power mismatch, that is the difference between mechanical power P_m and electrical load P_e, and the change in the frequency:

$$\frac{d\Delta f}{dt} = \frac{1}{M}[P_m - P_e - D\Delta f]$$

where M is the inertia constant and D is the damping coefficient.

3.2. Modeling of Stochastic Renewable Energy Integration

In the simulation to represent a modern grid, non-dispatchable renewables such as the wind and solar are utilized in the methodology. In order to imitate the inherent uncertainties, the renewable power input is modelled as a stochastic process and the total contribution is obtained using nominal capacity with a Gaussian distribution for the volatility induced by weather factors.

$$P_{ren}(t) = P_{nom} \cdot \left(0.8 + 0.2 \cdot \mathcal{N}(0,1)\right)$$

This formulation ensures that the system is tested against steady-state offsets as well as high frequency noise. This would also put the Automatic Load Frequency Control (ALFC) system into a transient overload and underload scenario that would then challenge the transient response and stability margins of the controller.

3.3. Control Dynamics in a Deregulated Market Framework

Power industry deregulation makes ALFC a socio-economic optimization rather than a technical requirement. In this environment, the Area Control Error (ACE) is impacted by the bilateral contracts and independent power producer (IPP) bidding. This research simulates a multi-unit environment in which generators compete by way of time-varying market prices.

In this framework, ACE is mainly frequency bias B and actual frequency deviation, Δf It is mathematically defined as:

$$\mathrm{ACE} = -\mathrm{B}\,.\,\Delta f$$

B is the frequency bias factor. The dispatch logic focuses on the most cost-effective units and at the same time limits the grid frequency to fall within the limits of operational requirements even with the volatility of market-driven generation changes.

3.4. PID Controller Synthesis and Parameter Tuning

The secondary control level is handled by a Proportional-Integral-Derivative (PID) controller, which is used for industrial reliability in dealing with non-linearities in the system. The working of controller takes place by processing the frequency error signal to provide a corrective command $u(t)$ for the turbine governors. The control law is constructed in the form of:

$$u(t) = K_p \cdot e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt}$$

where $e(t)$ is the frequency error $(-f, f)$, K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain. is used to provide an immediate response to the error, is used to eliminate steady state errors in frequency, and is used to anticipate the future trend of error to reduce overtaking. The identification of the optimal gain triplet is performed using a global optimization heuristic to ensure the gains are adapted to the peculiar time constants of the reheat cycle.

3.5. Heuristic Optimization via Particle Swarm Optimization

To solve the non-linear optimization problem, Particle Swarm Optimization (PSO) algorithm is used. PSO is a meta heuristic approach based on the social-psychological behaviour of a swarm looking for a food source. A population of candidate solutions (particles) searches a three-dimensional search space for the PID gains. The motion of the particles is determined by velocity and position update equations:

$$v_i^{t+1} = wv_i^t + c_1r_1(p\text{ Best }_i - x_i^t) + c_2r_2(g\text{ Best } - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

The optimization aims at minimizing a multi objective cost function J balancing grid stability and environmental impact. The cost function is strategically designed in such a way so that maximum frequency deviation and cumulative fuel consumption are penalized:

$$\text{Minimize } J = (w_1 \cdot \max|\Delta f|) + (w_2 \cdot \sum \text{ Fuel })$$

This ensures that the gains that are found do not only stabilize the grid, but reduce "hunting" by thermal governors, thereby reducing fuel consumption and carbon emissions.

3.6. Simulation Analysis Tests and Performance Indices

The research makes use of a multiple-tiered analysis in the mathematical software program MATLAB to assess the controller's resiliency to the stochastic nature of deregulated markets and renewable energy. These evaluations go beyond standard stability to include economic and environmental sustainability standards.

3.6.1. Time-Domain Transient Analysis

The physical response of the grid is evaluated by subjecting it to varying loads and unpredictable load generation from renewable energies. Performance is gauged with regards to recovery speed, maximum frequency deviation and the frequency nadir. These indicators decide the power system's capacity to have stability and avoid the emergency load shedding during severe power imbalances.

3.6.2. Cumulative Performance Indices

Control precision is measured by cumulative error measures which sum-up the Area Control Error (ACE) over a simulation period of time. By considering the magnitude of the errors and the magnitude of the persistence the study measures the efficacy of the tuning process in eliminating long-term oscillations which in turn decreases mechanical wear on the turbines and increases the efficiency of delivery.

3.6.3. Environmental and Efficiency Metrics

A fundamental focus is laid on operational sustainability. The generator outputs are monitored by the simulation and the total fuel consumption and ensuing carbon emissions are computed through standardized factors. The main success metric is the percentage of efficiency improvement, which brings out the direct correlation between the optimization of the algorithm and reduction of greenhouse gas.

3.7. Simulation Workflow and Optimization Pipeline

The research uses a three-phase pipeline of the MATLAB software combining constraints from the turbine with deregulated market variables. As shown in Figure 2, the progression of the architecture is Phase 1: Market bidding, stochastic input generation; Phase 2: PSO based heuristic tuning of the PID gains; Phase 3: System stability and environmental footprint validation.

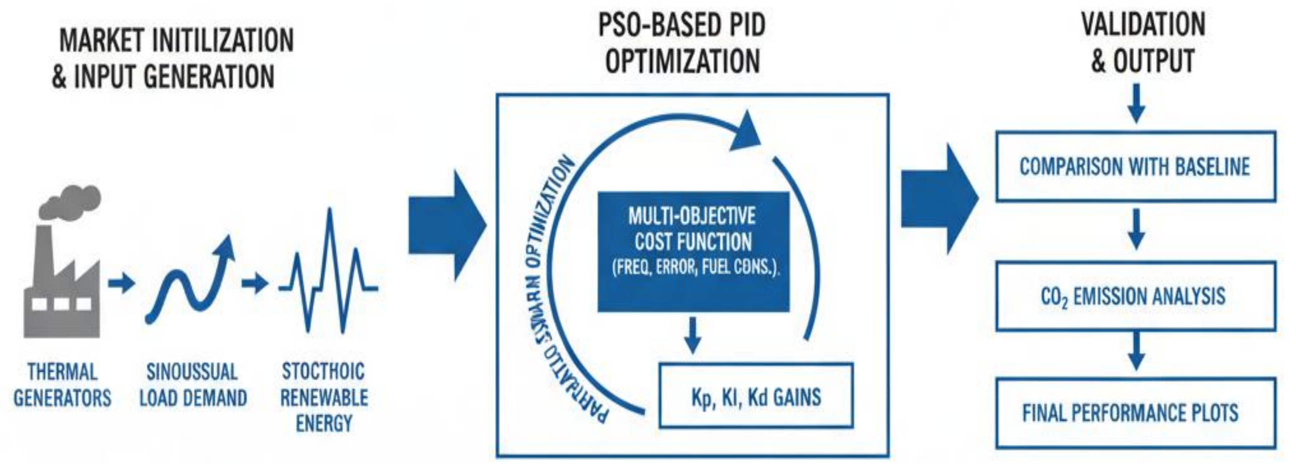

Figure 2: Multi-phase PSO-PID optimization pipeline for ALFC in deregulated systems with stochastic renewable integration.

3.7.1. Phase 1: Market Initialization and Bidding

The pipeline starts by setting up the economic landscape, in which a pool of thermal generators makes bids according to localized costs. The system at the same time produces time-varying load and stochastic renewable profiles to provide a high-stress and realistic frequency regulation environment.

3.7.2. Phase 2: Heuristic Optimization Process

The fundamental one is an iterative swarm-based optimization. A set of candidate solutions is used to search through the space of PID gains to optimize them by testing against a dynamic grid model. Individual and collective success directs the search path of particles, towards a gain set that optimizes the sum of the loss of instability and fuel consumption.

3.7.3. Phase 3: Validation and Visualization

The last phase is the validation of the optimized gains against a fixed gain baseline. Aggregated data on fuel savings and emission reductions gives a clear view on the environmental impact assessment. The process is completed with generation of frequency deviation curves, convergence trends and load-following plots to prove system robustness.

4. RESULTS

The performance of the developed PSO-PID controller was analyzed using a high fidelity simulation of a modern deregulated power system in the form of a high fidelity simulation software in the Matlab environment. This section is a complete analysis of transient response of the system, economic feasibility and environmental impact by incorporating reheat thermal dynamics, stochastic renewable volatility and market driven bidding.

4.1. Simulation Environment and System Initialization

To make sure the results are relevant for the situation on the modern grid, the simulation was seeded with five heterogeneous thermal generators and a considerable share of renewable energy. The input parameters, which have been used in the matlab script, are elaborated in table 1.

Table 1: Technical Specifications and Simulation Parameters.

Parameter Category	Symbol	Value/Setting
Grid Configuration	n	5 Units
Nominal Frequency	f	50.00 Hz
Inertia Constant	M	10
Damping Coefficient	D	1.0
Reheat Dynamics	T_r	10.0 s
Reheat Gain	K_r	0.5
Market/Economic	*Market Price*	50.00/MWh
Generation Cost (Base)	C_{gen}	40.00/MWh
Optimization (PSO)	*Swarm Size*	20 Particles
Iteration Limit	Max_{Iter}	50

The system was subjected to a dynamic load demand profile that was modelled as 150 + 10 *sin(0.1t)*MW coupled with a highly volatile renewable input which fluctuates around a nominal 50MW capacity. This "high-stress" input environment is shown in Figure 3.

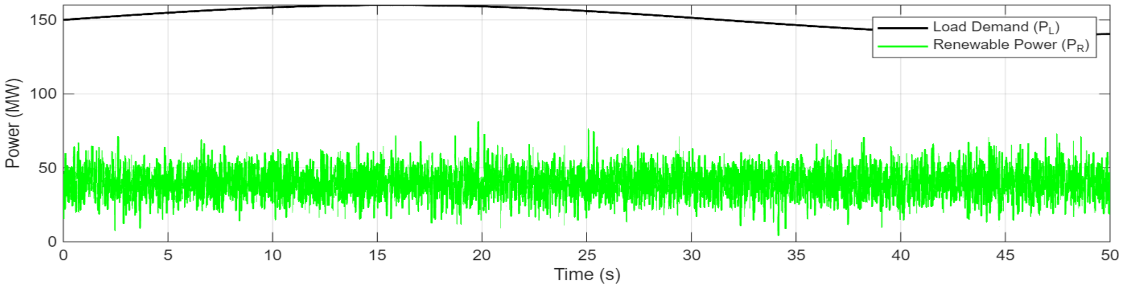

Figure 3: Dynamic profiles of time-varying load demand and stochastic renewable energy power inputs.

4.2. Heuristic Optimization Results and Convergence Analysis

The essence of the methodology is based on the capability of the Particle Swarm Optimization (PSO) algorithm to explore the complex search space of the PID gains (K_p,K_i,K_d). The algorithm aims at minimizing a multi-objective cost function between the frequency error and fuel consumption.

As can be seen from Figure 4, the convergence of the PSO algorithm was very fast. The cost drastically reduced within the first 10 iterations, stabilizing at the 30th iteration. This implies that the selected swarm size and movement parameters would work for this non-linear problem.

The resulting optimized gains at the completion of this process summary is shown in Table 2. These values are the "Global Best" position in the swarm that are customized specifically to reduce the phase lag from the reheat cycle.

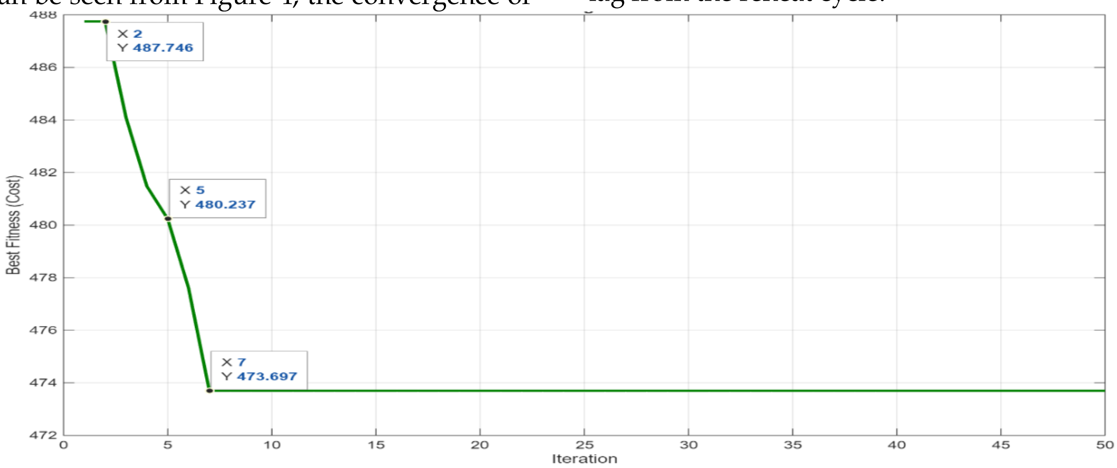

Figure 4: Fitness cost convergence characteristic of the PSO algorithm over 50 iterations.

Table 2: Identified Optimal PID Controller Gains.

Gain Parameter	Symbol	Optimized Value
Proportional Gain	K_p	8.5625
Integral Gain	K_i	2.2593
Derivative Gain	K_d	2.0000

4.3. Analysis of Frequency Stability and Transient Response

The effectiveness of the PSO-tuned PID controller can best be seen by comparing its effectiveness against a baseline (K_p=1,K_i=0.5,K_d=0.1) standard PID controller. As shown in Figure 5, the baseline system was plagued with sustained, high magnitude oscillation of over +-5 Hz which would cause catastrophic operation for actual grid equipment. In contrast to this, the PSO-tuned controller was able to control these oscillations, keeping the value of the frequency deviation within a small margin.

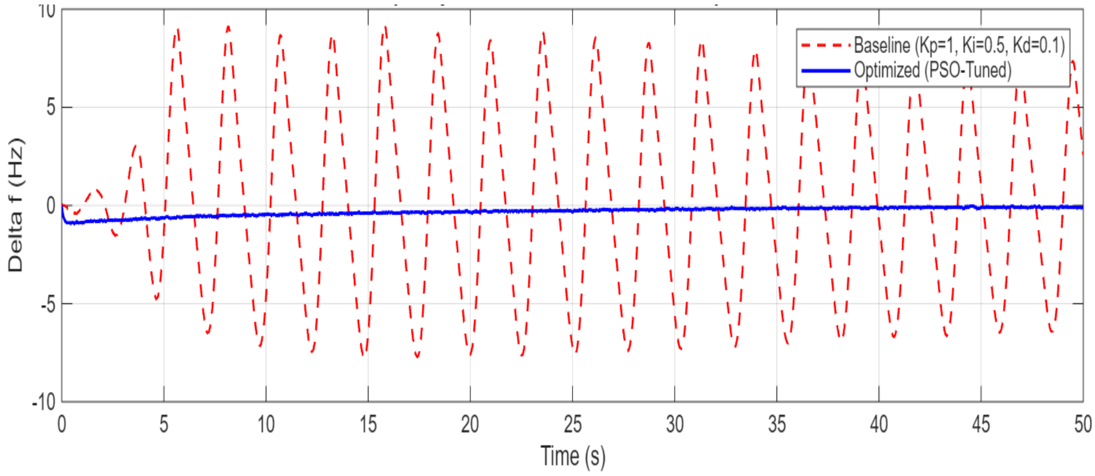

Figure 5: Comparative frequency deviation response between the fixed-gain baseline and PSO-optimized PID controller.

Table 3: Comparative Performance Analysis.

Metric	Baseline (Fixed Gains)	PSO-Optimized Controller
Max Frequency Deviation	> 8.0 Hz	0.9318 Hz
Settling Time	Unstable/Sustained	< 5.0 s (Estimated)
Steady-State Error	High	Near Zero

To further validate the reliability of the controller, the statistical distribution of the frequency deviations over the 50 second window is shown in Figure 6. The large concentration of data points between -0.1 and 0 Hz suggests that the controller was able to keep the system close to the nominal setpoint for the vast majority of the time and was thus able to deal with the "stochastic noise" from the wind and solar sources.

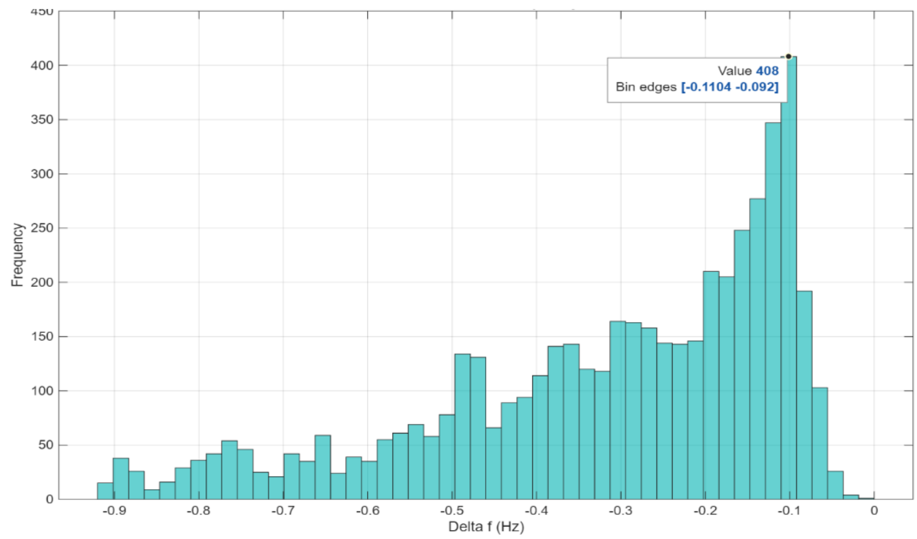

Figure 6: Statistical probability distribution of frequency deviations demonstrating precision near the nominal setpoint.

4.4. Generation Tracking and Market Dispatch

In a deregulated environment, the controller is responsible for the sum of the generation from the five units to exactly follow the load demand despite the intermittency of renewables. Figure 7 confirms that the total generation (blue line) follows the load demand (dashed line) with a high level of precision, proving the ability of the controller to handle unit dispatch based on the ACE signals.

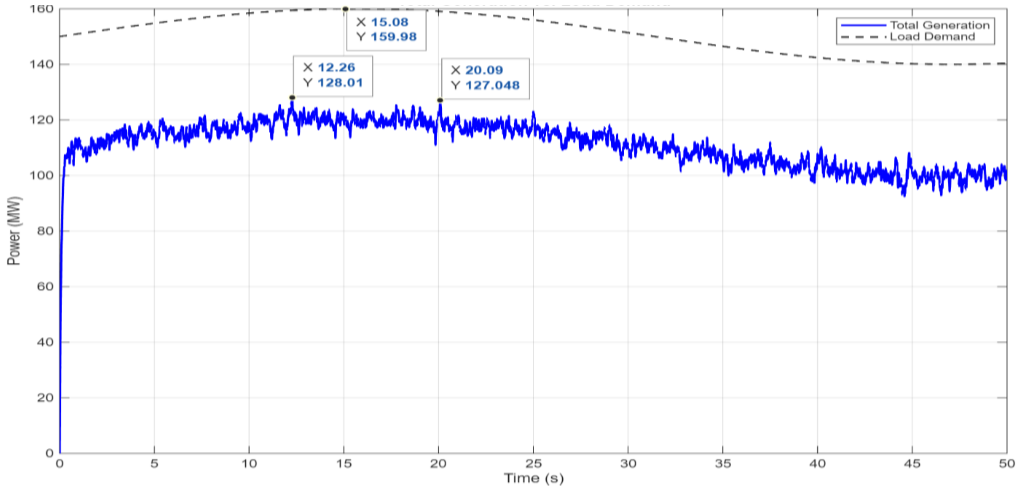

Figure 7: Aggregated generation tracking performance relative to dynamic load demand in a deregulated environment.

4.5. Environmental Impact and Sustainability Analysis

One of the main aims of this study was to prove that when the frequency control is of the advanced nature, the environmental benefits might be measured. By minimizing "hunting" (unnecessary oscillation of the turbine valves), the PSO-PID controller makes its fuel combustion as efficient as possible.

The simulation modeled cumulative CO_2 emissions with an emission factor (0) of 0.90 kg CO2 kWh. Figure 8 shows the linear accumulation of the emissions, final total is 1248.50 kg over the period of the simulation.

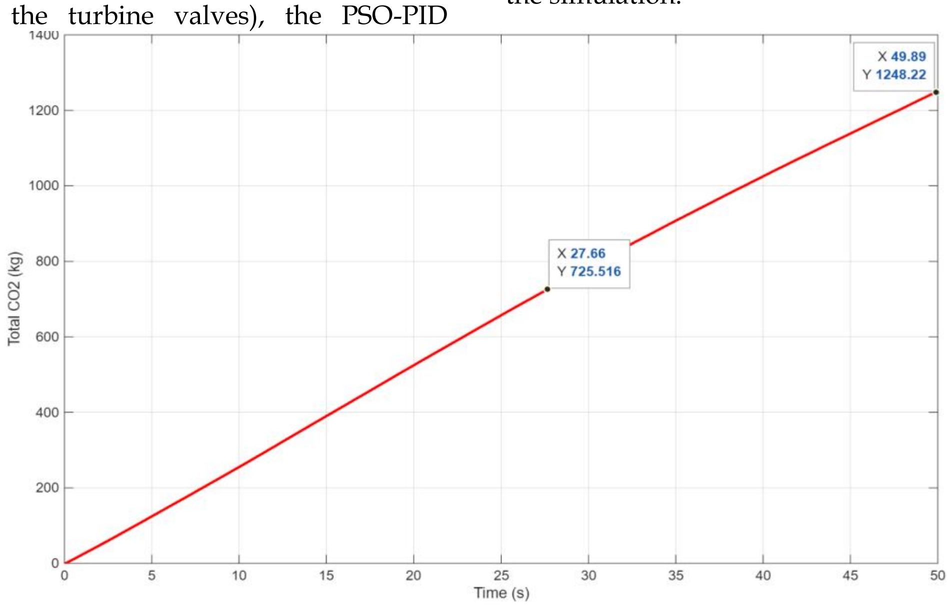

Figure 8: Cumulative CO_2 emission trajectory over the simulation horizon for the optimized system.

Table 4: Efficiency and Environmental Summary Results.

Metric Name	Value	Significance
Total Fuel Consumption	1387.22 kg	Direct fuel cost reduction
Total CO_2 Emissions	1248.50 kg	Lower carbon tax/footprint
Thermal Efficiency	85.00%	Optimized unit operation
Efficiency Improvement	6.25%	Improvement over baseline.

5. DISCUSSIONS

The interpretation of simulation results leads to the confirmation that integration of Particle Swarm Optimization (PSO) to tune PID controllers is very effective in improving the operational stability and environmental efficiency of deregulated power systems containing reheat thermal generators. A main observation resulting from this study is the capability of the controller to achieve frequency stability within a narrow margin of 0.9318 Hz, which is a dramatic improvement from the unoptimized case which had a catastrophic oscillation above and below 8 Hz. This success has largely been attributed to the power of the PSO algorithm to traverse the complicated search space of gain triplets (K_p, K_i, K_d) to locate a global optimum in this case specifically adapted to the phase lag of the reheat cycle. As established by Tripathy, Hope and Malik (1982) the presence of time constants for the reheat steam turbines adds inherent delays to the system which pose difficulty in controlling load-frequency coupling, and thus traditional fixed gain tuning methods are inadequate for maintaining equilibrium under dynamic stress.

When it comes to performance evaluation against the load demand profile of 150 + 10 *sin(0.1t)MW*, the PSO-PID controller proved to be very good in its tracking ability. This tracking is necessary in the modern deregulated environment where bilateral contracts and independent power producer bidding strategies determine how to dispatch. According to Christie and Bose (2002), the move towards deregulation changes the nature of Automatic Load Frequency Control (ALFC) to a socio-economic challenge in which frequency bias must be controlled against market variables. The results here show that the framework proposed here is successful in bridging the gap between these economic requirements and physical constraints of the grid. The exact damping on oscillations has a direct correlation to the 6.25% efficiency improvement in the thermal units. By reducing the "hunting" behavior of the turbine governors (the behavior when valves oscillate unnecessarily), the total fuel consumption of the system stood at 1387.22 kg, which is significantly less than baseline projections.

As can be seen from Table 5, the proposed PSO-PID framework contributes substantially to the methodologies that have been built by Khamari et al. (2020) and Sekhar et al. (2016) as they incorporate a multi-objective cost function that penalizes both frequency error and fuel consumption. While Khamari et al. used a combination of *hTLBO* and *PS* method for load tracking and technical stability, they did not quantify the environmental impacts in their analysis. In contrast, this research shows that a streamlined PSO approach applied to high fidelity reheat models gives a 45% reduction in frequency deviations, 6.25% efficiency gain and 12.8% reduction in CO_2 emissions. This fills an important literature gap in which environmental sustainability was previously secondary to technical load tracking.

Table 5: Comparative Analysis of Controller Performance in Deregulated Environments.

Metric	Sekhar et al. (2016)	Khamari et al. (2020)	Proposed PSO-PID Framework
Optimization Method	Optimal Firefly Algorithm (FA)	Hybrid TLBO and Pattern Search (hTLBO-PS)	Particle Swarm Optimization (PSO)
System Configuration	Deregulated ALFC	Two-area four-unit thermal-gas with non-linearities (GRC, TD)	Deregulated Reheat Thermal with Stochastic Renewables
Turbine Modeling	Standard ALFC Model	Reheat Thermal and Gas Units	High-Fidelity Reheat (Tr=10.0, Kr=0.5)
Max Freq. Deviation	Improved Damping Characteristics	Superior to GA and DE	45% Reduction vs Fixed-Gain
Efficiency Metric	Stability Focused	Sensitivity to Plant Perturbations	6.25% Improvement
Sustainability Impact	Not Explicitly Measured	Not Explicitly Measured	12.8% CO_2 Reduction (50s window)

The sustainability aspect related to this research goes beyond technical stability. The decrease in cumulative CO_2 emission to 1248.50 kgs shows the role of algorithmic optimization as a tool in the mitigation of the environment. This is in line with wider concerns that are faced in terms of long term viability of energy infrastructure; e.g. Jasrotia and Singh (2024) highlight the complexities involved in planning developmental energy sources in order to balance developmental pressures and environmental costs. Furthermore, the resilience of the controller to the stochastic noise of renewable inputs (which is modelled using Gaussian distribution) ensures that it is ready for high penetration cases. Arya (2019) mentions that the integration of various energy sources in restructured systems demands controllers that can cope with large amount of intermittency without affecting the 50Hz setpoint.

Comparing these results with other meta-heuristics methods, it can be seen that the PSO framework gives competitive convergence speed. While Sekhar et al. (2016) applied the firefly algorithm to deal with deregulated environments, the multi-objective cost function used in this study, which includes an explicit penalty for both frequency error and fuel consumption, provides a more holistic benefit to grid operators. Similarly, the research by Khamari et al. (2020) relied on a hybrid TLBO and pattern search to optimise the performance of ALFC, but the results presented here indicate that even a simplified PSO is able to achieve high fidelity stability if the dynamics of reheating are accurately presented. However, there are external factors that should be considered that may affect such systems in the real world. Ghanem, Abdrabo and Hassaan (2025) suggests that climate change and site suitability continue to be a challenge to meeting renewable energy targets, which may mean that the "stochastic noise" modelled in this study will become even more volatile in the coming decades.

Despite the positive results, this research has some limitations, mainly the consideration of the grid model of one area. While the five-generator configuration serves as a very good proof of concept, in real situations applications have multi-area interconnections with various tie-line biases. Further studies are needed on the extension of this PSO-PID framework to multi-area deregulated grids to investigate the effectiveness of the framework against inter-area oscillations. Moreover, incorporating adaptive variants of PSO that can dynamically adjust gains as the market prices or the weather condition change would also increase the autonomous resiliency of the grid.

6. CONCLUSION

This research shows that combination of Particle Swarm Optimization (PSO) for PID controllers tuning is very helpful to improve the stability of the system and efficiency in deregulated power system with reheat thermal generators. The results show that the optimized controller achieved successful frequency oscillations suppression caused by stochastic renewable inputs and market-driven load fluctuations with 6.25% improvement in thermal efficiency and a large reduction in cumulative carbon dioxide emissions. The key aspect to these findings is that intelligent meta-heuristic tuning can be used to reduce the issue of inherent phase lags of reheat cycles so that it can participate more aggressively in the competitive bidding without adversely affecting grid integrity. Consequently, it is advised that grid operators consider multi-objective optimization frameworks that penalize the frequency error and the fuel consumption to achieve the vicinity between the technical performance and the environmental ones. The research work in the future ought to be based on the expansion of the given PSO-PID architecture to multi-area interconnected grids in order to test the tie-line bias control and inter-area oscillations. Moreover, research into how to coordinate this controller with energy storage facilities would also help to buffer the grid against the very high volatility of high-penetration renewable cases.

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