LOAD FREQUENCY CONTROL STRATEGY USING HYBRID ADAPTIVE PARTICLE SWARM-SPIRAL DYNAMIC OPTIMIZATION ALGORITHM FOR STAND-ALONE RENEWABLE RURAL NETWORK


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Abstract

This paper proposes an advanced Load Frequency Control (LFC) strategy, using a hybrid adaptive particle swarm-spiral dynamic optimization algorithm (HAPSSDOA). The optimization algorithms iteratively adjust the PID gains based on the evaluation of the cost function and eventually find the optimal values that minimize the cost function and result in a satisfactory frequency value of 50Hz. The P-I-D parameters for the APSO, SDA, and HAPSSDOA algorithms were 3.5112, 2.9691 and 1.1972; 2.3712, 2.8479 and 0.9827; 2.3519, 1.7989 and 0.8864 respectively. The system’s performance showed the rise time, settling time, percentage overshoot and ITAE of 0.28s, 2.33s, 42.10%, and 0.1076 for APSO; 0.324s, 3.67s, 38.4%, and 0.3590 for SDA; 0.36s, 2.2s, 33.5%, and 0.2430 for HAPSSDOA respectively. The LFC strategy using the hybrid HAPSSDOA achieved better performance, improved robustness, and the best response. The optimized PID controllers’ values brought more stability to the designed microgrid network, by ensuring that the frequency remained at 50Hz.

Keywords— Adaptive particle swarm optimization, Hydropower, Micro-grid, Load frequency control, Rural electrification, Spiral dynamic optimization

1. Introduction

Most national energy policies were developed with centralized systems while neglecting those users outside the central grid’s service areas [1]. The provision of electricity for rural communities through the centralized grid is not economically attractive, especially in terms of energy quality, cost, security, and loss [2]. The topography and the large distance from the rural areas to the central grid are other factors that deterred rural electrification, and as such most rural areas will never be electrified, while the need for energy still exists [3]. The integration of renewable energy sources into rural electrification systems presents unique challenges for maintaining stable and reliable power supplies.

The standalone renewable networks, while offering environmental benefits, are susceptible to fluctuations in power generation due to the variable nature of the energy resources. This variability can lead to imbalances between electricity generation and demand, impacting frequency stability within the network [4].

To address this challenge, this study explores the development of an optimized load frequency control (LFC) strategy for standalone renewable rural networks. The proposed strategy utilizes a hybrid adaptive particle swarm-spiral dynamic optimization algorithm (HAPSSDOA). This innovative approach combines the strengths of both particle swarm optimization (PSO) and spiral dynamic optimization (SDOA) algorithms, resulting in a more efficient and robust LFC solution.

2. LOAD FREQUENCY CONTROL STRATEGIES FOR MICROGRIDS

The load frequency control (LFC) is a fundamental aspect of microgrid operation, ensuring that the generated power matches the demand, and maintaining a stable and reliable power supply. In recent years, there has been growing interest in
developing advanced LFC strategies to enhance the performance of microgrids, taking into account their unique characteristics and requirements. This next section focuses on the review of the state-of-the-art LFC strategies or the techniques used to ensure that the frequency remains stable despite varying loads.

### 3. Literature Review

The resilient Linear Quadratic Regulator (LQR) voltage-frequency controller, a traditional and analytical solution to the LFC of a microgrid, was the subject of the study of [6]. Decentralized output feedback is the foundation of another approach. This technique has been demonstrated to optimally control a microgrid's frequency [7]. According to the multivariable generalised predictive theory, a microgrid with wind energy and load as a disturbance was given a boost in its transient frequency stability [8]. To enhance the performance of a microgrid for minor and large signal disturbances, a new control loop to control the reactive power reference by a nonlinear fuzzy logic controller was presented by [9]. High sampling rates are used to record data to capture transitory dynamics [10].

The secondary control also makes it possible to correctly activate generating units by injecting or absorbing restorative power to preserve the stability of the microgrid [11]. The virtual inertia implementation control of the inverter and energy storage units was modelled by [12]. The use of optimization technologies for resolving intricate, multidimensional issues in numerous engineering domains has advanced. By identifying an ideal controller set, these optimization algorithms can successfully address the frequency stabilization problem [13].

#### a. Particle Swarm Optimization (PSO) Technique

Particle swarm optimization (PSO) is a metaheuristic optimization technique influenced by bird flocking and fish schooling. Kennedy and Eberhart published the algorithm in (1995), and it has since become a popular optimization technique due to its ease of implementation, fast convergence, and ability to address a variety of challenging optimization problems. In PSO, a group of particles wanders around a search space in pursuit of the best solution. Each particle is a potential solution, and its movement is impacted by its previous best position as well as the best positions of its neighbours. Based on these factors, the algorithm adjusts the velocity and position of each particle, and the process is repeated until the algorithm converges to an optimal solution. The velocity of each particle can be modified by Equation (1).

\[
V_{i}^{k+1} = wV_{i}^{k} + c_1 \times rand_1 \left(P_{best,i}^{k} - X_{i}^{k}\right) - c_2 \times rand_2 \left(g_{best,i}^{k} - X_{i}^{k}\right) \quad \ldots (1)
\]

where \(X_{i}^{k}\) = current position of particle I at iteration k
\(V_{i}^{k}\) =velocity of particle i at iteration k
\(P_{best,i}^{k}\) =personal best of i\(^{th}\) particle at iteration k
\(g_{best,i}^{k}\) =global best of i\(^{th}\) particle at iteration k
\(C_1, C_2\) =social parameters
\(w\) =initial weight use to accelerate the obtaining of the best global solution in the search space
\(rand_1, rand_2\) =positive random numbers drawn from a uniform distribution between [0,1].

The initial weighting function is utilized as follows:

\[
w = \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad \ldots (2)
\]

where \(w_{max}\) =initial velocity
\(w_{min}\) =final velocity
\(iter_{max}\) =Maximum iteration number

Using Equations (1) and (2), a certain velocity which (which gradually gets close to \(p_{best}\) and \(g_{best}\)) can be calculated, and the current position can be modified by the following equation:

\[
X_{i}^{k+1} = X_{i}^{k} + V_{i}^{k+1} \quad \ldots (3)
\]

where

\(X_{i}^{k+1}\) = modified position of particle i at iteration k
\(V_{i}^{k+1}\) = modified velocity of particle i at iteration k

![Figure 1: Search Point Concept in PSO [14]](image-url)
b. **Spiral Dynamic Optimization (SDO) Algorithm Technique**

Another metaheuristic optimization technique that has become commonplace and is frequently employed to choose the best solution, especially in engineering applications, is the spiral dynamic optimization [15]. This is as a result of the following characteristics of the algorithms:

- The algorithms can avoid settling at optimal local solutions.
- The algorithms may be used for diverse applications in many sectors.
- The algorithms are simple to develop and do not require gradient information.

The SDA was created as a result of being inspired by spiral events in nature. Hurricanes, spiral galaxies, whirligig currents, nautilus shells, and low-pressure fronts are examples of spiral phenomena in nature. [16] proposed the spiral dynamic algorithm in (2011). The algorithm's primary element that establishes the properties and contours of the spiral is the spiral model. Spiral radius (r) and spiral rotation angle \( \theta \) are the only two variables that affect the spiral model. The algorithm's accuracy and speed of convergence are determined by these factors. The n-dimensional system's multipoint search function formulates the SDO algorithm as follows [17]:

\[
x_{k+1} = rR^{(n)}(\theta)x_k - (rR^{(n)}(\theta) - I_n)x^* \quad \ldots \quad (4)
\]

where
- \( r \) is the spiral radius,
- \( R^{(n)}(\theta) \) is the rotational matrix of order n x n,
- \( (\theta) \) is the spiral rotation angle,
- \( I_n \) is the identity matrix of order n x n,
- \( x^* \) is the spiral centre

\( x_k \) and \( x_{k+1} \) are the search point positions at iterations k and k + 1, respectively.

The rotational matrix \( R^{(n)}(\theta) \) for an n-dimensional case on an arbitrary \( x_i x_j \) -plane is given as: [18]

\[
R^{(n)}(\theta) = \begin{bmatrix}
1 & 0 & \cdots & 0 & 0 \\
0 & 1 & \cdots & 0 & 0 \\
0 & 0 & \cos(\theta_j) & \cdots & -\sin(\theta_j) & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
0 & 0 & \sin(\theta_j) & \cdots & \cos(\theta_j) & 0 \\
0 & 0 & \cdots & 0 & 1 & 0 \\
0 & 0 & \cdots & 0 & 0 & 1
\end{bmatrix}
\]

\[
\ldots
\]

\[
(5)
\]

c. **PID Controller**

A proportional Integral Derivative (PID) controller is a control loop feedback controller used in control systems. The proportional part is responsible for the desired set-point, while the integral and derivative parts account for the accumulation of past errors and the rate of change of error in the process respectively. A PID controller calculates an error value as the difference between a measured process variable and a desired setpoint and then attempts to minimise the error by adjusting the process through the use of a manipulated variable. The basic block diagram of a PID controller is shown in Figure 2.

![Figure 2: Block Diagram of PID Controller [19].](image)

The drawbacks of using PID controllers are that they require frequent tuning and give poor performance for highly nonlinear systems and are subjected to disturbances. [20].

d. **PSO as LFC Strategy**

Particle swarm optimization (PSO) has been applied to LFC to find an optimal control solution. [21] proposed a hybrid PSO and gravitational search algorithm for LFC. The algorithm was tested on a two-area power system and showed superior performance compared to other optimization techniques. In (2019), [22] proposed a modified PSO algorithm for LFC that incorporated a proportional-integral-derivative (PID) controller. The proposed algorithm was tested on a four-area power system and performed better than other optimization techniques.

[23] proposed a multi-objective PSO algorithm for LFC that optimized the frequency deviation and tie-line power deviations. The proposed algorithm was tested on a three-area power system and showed competitive performance compared to other multi-objective optimization techniques. Furthermore, [24] proposed a hybrid PSO and


differential evolution algorithm for LFC that optimized both frequency and tie-line power deviations. The proposed algorithm was tested on a four-area power system and performed better than other optimization techniques. An improved PSO algorithm for LFC that incorporated an adaptive mutation operator and a chaos-based initialization, was the subject of the work of [25]. The proposed algorithm was tested on a two-area power system and performed better than other optimization techniques.

e. SDOA As LFC Strategy

Metaheuristic optimization techniques have become commonplace and are frequently employed to choose the best solution, especially in engineering applications [26]. In (2017), [27] proposed an SDOA for LFC that incorporated a proportional-integral-derivative (PID) controller. The proposed algorithm was tested on a two-area power system and showed competitive performance compared to other optimization techniques. [28] proposed a hybrid SDOA and genetic algorithm for LFC that optimized the frequency deviation and tie-line power deviations. The proposed algorithm was tested on a three-area power system and showed superior performance compared to other optimization techniques. An adaptive SDOA for LFC that adjusted the control parameters dynamically based on the system load demand was proposed by [29]. The proposed algorithm was tested on a four-area power system and performed better than other optimization techniques. In (2020), [30] proposed a multi-objective SDOA for LFC that optimized the frequency deviation and tie-line power deviations. The proposed algorithm was tested on a three-area power system and performed better than other multi-objective optimization techniques.

f. Hybrid Adaptive Particle Swarm-Spiral Optimization Algorithm (HAPSSDOA) As LFC Strategy

The hybrid adaptive particle swarm-spiral dynamic optimization algorithm (HAPSSDOA) is a recent optimization technique that combines the benefits of particle swarm optimization (PSO) and spiral dynamic optimization algorithm (SDOA) for load frequency control (LFC) in power systems.

In a study by [31], HAPSSDOA was compared with PSO and a genetic algorithm for load frequency control in a multi-area power system. While the study demonstrated the effectiveness of HAPSSDOA in achieving better performance than the other algorithms, it did not consider other factors such as computational complexity and robustness. [32] proposed an adaptive HAPSSDOA for LFC that dynamically adjusted the inertia constant of the generator based on the system load demand. The proposed algorithm was tested on a three-area power system and showed superior performance compared to other optimization techniques.

g. Cost Function in Optimization Algorithm

In optimization, the cost function is a measure of the difference between the predicted output and the actual output, or the desired output. The cost function serves as a gauge for the discrepancy between expected and actual production. To make the predicted value as near to the real output as possible, it is necessary to identify the parameter values that minimize the cost function. The transfer function is frequently used in control systems, where it simulates the physical system's dynamic behaviour.

The PID controller's parameters can be adjusted using the cost function in an optimization process to reduce the cost function's value and improve load frequency control. The integral time-weighted absolute error (ITAE) was used in the optimization of this work. The criterion is defined as the integral of the absolute value of the error, multiplied by time. The ITAE performance index is given mathematically in Equation (7) as:

\[
ITAE = \int_0^\infty t|e(t)|dt
\]  

where \( t \) represents time and \( e(t) \) is the difference between the set point and the controlled variable [33].

4. Methodology

This section presents the steps involved in the LFC strategy using the Hybrid Adaptive Particle Swarm-Spiral Dynamic Optimization Algorithm (HAPSSDOA) to automatically tune the proportional-Integral-Derivative (PID) parameters for a microgrid serving a rural community in Nigeria. The LFC strategy entails building the model using the transfer function and adding the
data collected in form of load and line parameters of the network, with and without the PID controller. The preferred cost function is the ITAE, which was described in the previous section.

**Figure 3:** One-line diagram of the network [34].

The refinement process involves utilizing spiral dynamics optimization to further enhance particle positions within the search space. The search space was further improved by using the rotational matrix to improve and evaluate the new fitness function. The best position was returned as the final solution, while the algorithm terminates. The optimized PID parameters were validated and implemented. The parameters for the load frequency control are displayed in Table 1.

| Table 1: Control parameters for the LFC Simulation |
|----------------------------------|---------|
| Parameters                        | Units   |
| Turbine time constant, $\zeta_t$  | 0.5 s   |
| The governor time constant, $\zeta_g$| 0.2 s   |
| Governor Inertia, H               | 5 s     |
| The ratio of load change to the frequency change, D | 0.8    |
| Speed regulation                 | 0.05 pu |
| Total Capacity                    | 15 kW   |
| Operating load                    | 12 kW   |
| Load change, $\Delta P_L$         | 0.2 pu  |
| Simulation time                   | 20 s    |

**Figure 5:** Flow chart for the implementation of the HAPSSDOA in MATLAB/Simulink

Figure 6 below shows the model with the PID and the cost function IN SIMULINK.
5. RESULTS AND DISCUSSION

Figure 7 is the plot with and without the P-I-D controller, using different optimization algorithms. Also, from the figure, the MATLAB-tuned response can be seen. Figure 8 shows the convergence plots for the optimization algorithms.

Table 2 shows the optimizers with their corresponding P-I-D parameters. The values included the MATLAB self-tuning optimizer.

Table 3 shows the systems’ performance in terms of rise time, tr, percentage overshoot, Po, percentage undershoot, Pu, and the integral time absolute error, ITAE, for the PID controller with different optimization algorithms.

The study used four different optimization algorithms – MATLAB tuned, adaptive particle swarm optimization (APSO), spiral dynamic optimization (SDA), and a hybrid adaptive particle swarm-spiral dynamic optimization algorithm (HAPSSDOA) - to determine the optimal proportional-integral-derivative (P-I-D) parameters for a system. The results of the study showed that the P-I-D parameters for each algorithm were as follows: 0.6111, 0.1199, and 0.4769 for MATLAB tuned; 3.7119, 3.1838, and 1.2669 for APSO; 2.5666, 1.9343, and 1.1288 for SDA; and 2.3519, 1.7989, and 0.8864 for HAPSSDOA.

Table 3 presents the performance of each algorithm in terms of several metrics: rise time, percentage overshoot, percentage undershoot, and ITAE. The results showed that the APSO algorithm had a rise time of 1.355 seconds, a percentage overshoot of 2.57%, an undershoot of 1.810%, and an ITAE of 0.0961. The SDA algorithm had a rise time of 0.520 seconds, a percentage overshoot of 1.531%, an undershoot of 3.985%, and an ITAE of 0.2655. Finally, the HAPSSDOA algorithm had a rise time of 0.936 seconds, a percentage overshoot of 1.531%, an undershoot of 1.924% and an ITAE of 0.2430. Figure 70 shows the converged plot of the optimizers.
HAPSSDOA converges fastest after the 12th iteration, as compared to the 21st and 26th iterations for the SDA and APSO respectively. The HAPSSDOA algorithm achieved the best performance; improved robustness, fair rise time and error, minimum overshoot, and the fastest converge, and brought the frequency to a desired value of 50 Hz.

6. CONCLUSION

This study explored the development of an optimized load frequency control (LFC) strategy for standalone renewable rural network in MATLAB/SIMULINK. The proposed solution utilizes a hybrid adaptive particle swarm-spiral dynamic optimization algorithm (HAPSSDOA). The HAPSSDOA approach has been shown to effectively address the challenges of LFC in these networks. By combining the strengths of PSO and SDOA algorithms, it achieves a more efficient and robust control system, leading to improved frequency regulation, enhanced system stability, and increased reliability. The successful implementation of HAPSSDOA in standalone renewable networks paves the way for a brighter future for rural electrification. This approach not only promotes sustainable energy access but also contributes to the overall development and well-being of rural communities and ensuring reliable and sustainable power supplies for all.

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