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Enhancing Power Flow Control: A Comparative Study of Genetic Algorithm and Particle Swarm Optimization

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Abstract:

This research investigates the enhancement of power quality in power systems through the application of Soft Computing Techniques, with a particular focus on addressing the Optimal Power Flow (OPF) problem, known for its nonlinear optimization complexity within power systems. A novel hybrid optimization approach, combining the Genetic Algorithm (GA) with the Particle Swarm Optimization (PSO) technique, is introduced to tackle this challenge. This hybridization is designed to capitalize on the strengths of both methods, with the overarching goal of achieving environmental, technical, and economic benefits. The study explores both single and multi-objective optimization scenarios, encompassing diverse objectives such as minimizing generation costs, reducing emissions, minimizing transmission power losses, and maximizing voltage stability and profiles. Experimental validation of the developed PSO-GA hybrid algorithm is conducted on three standard bus systems, demonstrating significant enhancements in the efficiency and reliability of OPF outcomes. Notably, the hybrid technique showcases superior levels of techno-economic-environmental advantages compared to conventional methods. Additionally, sensitivity analysis confirms the robustness of the proposed algorithm against parameter variations. In conclusion, this research underscores the potential of integrating Soft Computing Techniques to effectively optimize power systems and elevate power quality.

1. Introduction:

Imagine the power grid as a complex network of roads, where electricity flows instead of cars. Finding the most efficient paths for this flow is crucial for both saving money and ensuring reliable power delivery. This is where Optimal Power Flow (OPF) comes in. Optimal Power Flow (OPF) is an optimization technique that helps power companies operate their grids efficiently. Traditionally, simplifying the problem led to inaccuracies. Now, however, newer methods use advanced mathematical tools to capture the real-world complexity of power systems, leading to better decision-making.Power companies aren't just focused on minimizing costs anymore. They also want to consider additional objectives like reducing emissions or integrating renewable energy sources, while still respecting system limitations. This makes OPF even more important, as it can handle these multi-faceted goals.Think of OPF as a complex puzzle with many interconnected pieces. Solving it involves determining the optimal settings for various power system elements, considering all the goals and constraints. By using advanced optimization techniques, OPF can unlock significant economic and engineering benefits for the power industry.The heart of Optimal Power Flow (OPF) is finding the best settings for various power system elements, like generator voltages and outputs, to achieve a specific goal. This goal could be minimizing fuel costs, reducing power loss, or keeping voltage levels stable, all while obeying system limitations.Traditional OPF uses complex equations based on physics and network topology. Its difficulty arises from non-linear constraints and many interacting variables, making it a challenging puzzle to solve efficiently.This research paper is a new approach: combining two optimization techniques, Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), into a hybrid method. This method aims to leverage the strengths of both techniques for better performance.The proposed method is tested on different power system models, comparing its results to individual GA and PSO approaches. This comparison will assess if the hybrid method indeed performs better, particularly in handling both continuous and discrete control variables.

2. Literature Review:

In 2020, several advancements were made in tackling the complex Optimal Power Flow (OPF) problem. Zhao Yuan and Mario Paolone [1] proposed a second-order cone ACOPF (SOC-ACOPF) model with improved relaxation for handling transmission line losses. Shuijia Li et al. [2] introduced a self-adaptive penalty constraint handling method within the JADE algorithm (EJADE-SP) to enhance its performance for OPF. Hossein Saberi et al. ([3]) extended the SCOPF problem with DC load flow formulations to consider transient stability margins using a heuristic decomposition method. Fariba Zohrizadeh et al. ([4]) reviewed conic optimization techniques for power systems, including linear programming, second-order cone programming, and semi-definite programming, alongside solution methods like interior-point techniques and first-order methods. Warid Warid ([5]) proposed the AMTPG-Jaya algorithm, a metaheuristic optimizer, for addressing various single-objective OPF models. Finally, Mengxia Wang et al. ([6]) developed the OPFCTTB model considering transient thermal behavior of overhead lines and utilized the PDIPM method for its solution.

3. Methodology

In power systems, Optimal Power Flow (OPF) presents a challenging optimization problem due to its non-convex and non-linear nature. It aims to minimize specific objectives subject to various operational constraints, both equalities and inequalities. Solving OPF accurately and efficiently remains a crucial yet computationally demanding task in power system analysis. By optimizing key performance metrics while adhering to these constraints, OPF plays a vital role in ensuring reliable and efficient operation of the power grid.

Objective Functions

The Optimal Power Flow (OPF) problem deals with minimizing multiple objectives, which can be represented mathematically as:

Minimize f(y) = {f1(y), f2(y), ..., fn(y)} (1)

Subject to:

G(y) ≥ 0, i = 0, 1, ..., m (Operational inequality constraints) (2)

H(y) ≥ 0, i = 0, 1, ..., p (Equality constraints) (3)

Li ≤ yi ≤ Ui, i = 0, 1, ..., n (Boundary constraints) (4)

Equation 1 represents the objective functions, while Equations 2-4 represent the operational constraints, equality constraints, and boundary constraints, respectively. These objective functions can be categorized as economic, technical, and environmental.

Common objective functions include:

Economic: Minimize fuel cost (most common), which is a quadratic function of generated real power (Equation 5).

$$minF1 = \sum_{i=1}^{Ng}(a_i P_{gi}^2 + bP_{gi} + ci₹/hr) \quad (5)$$

Technical: Minimize transmission power loss (Equation 6)

$$minF2(y) = \sum_{i=1}^{N} \left(G_k U_i^2 + U_j^2 - 2U_i U_j cos\partial_{ij}\right) \tag{6}$$

Minimize voltage deviation at load buses (Equation 7).

$$F3(y) = \Delta U = \sum_{n=1}^{Nbus} |U - 1| \tag{7}$$

Environmental: Minimize total emissions (Equation 8).

$$F4 = \sum_{i=1}^{Ng} 10^{-2}\left(a_i + \beta_i P_{gi} + yP_{gi}^2\right) + |\varepsilon_i \exp\,[\wedge_i\, P_{gi}] \tag{8}$$

Additionally, improving voltage stability is often achieved by minimizing the Voltage Stability Index (Lindex), it is stated as follows:

$$L_i = |1 - \sum_{i=1}^{Ng} F_{ji} \frac{U_i}{U_j} < \left(\theta_{ij} + \delta_i - \delta_j\right)$$
(9)

$$F_{ji} = [X_{LL}]^{-1}[X_{LG}] \tag{10}$$

Hence, the 5th objective function (F5) seeks to minimize the maximumL-index across all elements in the system (j = 1, 2, ..., Nb), as expressed in equation (11):

$$L_5 = Max\left(L_j\right) \quad j = 1,2 \dots \dots \dots, N_b \tag{11}$$

4.1 Efficient Optimal Power Flow with a Hybrid Genetic Algorithm and Particle Swarm Optimization

Classical Genetic Algorithm

Imagine harnessing the power of evolution to solve complex problems! Inspired by natural selection, Genetic Algorithms (GAs) [9] do just that. They excel at finding optimal solutions for various optimization tasks [10].

Here's how GAs work:

1. Start with a population of candidate solutions. Each solution represents a potential answer to the problem.
2. Evaluate each solution's "fitness" - how well it solves the problem. Solutions with higher fitness are more likely to survive.
3. Perform genetic operations:
    - Selection: Pick "fitter" solutions to reproduce, like natural selection.
    - Crossover: Combine parts of parents to create new offspring with diverse traits.
    - Mutation: Introduce random changes to explore new possibilities.
4. Repeat steps 2 and 3: Create new generations, gradually improving the population's fitness.

This process eventually leads to a population consisting mainly of high-performing solutions, potentially near the optimal solution

The selection probability of every individual is:

$$P_i = \frac{f_i}{\sum_{i=1}^{N} f_i} \; ; \; f_i = \frac{k}{f_i} \tag{12}$$

Equation (12) introduces a coefficient (k) that balances the influence of individual fitness values (Fi) during the selection process. Equation (13) then details the specific method used to combine genetic material from selected chromosomes, known as chromosome crossing.

$$\begin{cases} b_{kj} = b_{kj}.(1-a) + b_{ij}.a \\ b_{lj} = b_{lj}.(1-a) + b_{kj}.a \end{cases} \tag{13}$$

After careful selection, the jth gene of the ith individual has been chosen for mutation! This means its value will be altered slightly, potentially leading to a better solution.

$$b_{ij} = \begin{cases} b_{ij} + \left(b_{ij} - b_{max}\right).f(g)\ r > 0.5 \\ b_{lj} + \left(b_{min} - b_{ij}\right).f(g)\ r \leq 0.5 \end{cases} \tag{14}$$

In equation (14), “g” indicates the current iteration number, “r” indicates a random number, “Gmax” indicates the highest number of evolutions

$$\mathrm{f(g)} = r(l - g/G_{max})^2 \tag{15}$$

4.2 Classical PSO Approach

Imagine a flock of birds searching for food, sharing information and dynamically adapting their flight based on individual and group knowledge. This inspiration fuels the **Particle Swarm Optimization (PSO) technique**, an optimization method developed in [11].

In PSO, each bird represents a possible solution to a problem. They "fly" through the search space, influenced by their own past experience (**personal best**) and the best positions found by the entire swarm (**global best**). This collaborative learning helps them gradually converge towards the optimal solution.

The process starts with a random swarm of particles. Each particle updates its position and velocity based on its personal best and the best position found by any particle in the swarm. Equations (24) and (25) define how these updates occur.

$$\mathrm{U}_{k+1} = u_k + c_1\left(P_{best_k} - y_k\right) + c_2(G_{best_k} - y_k) \tag{16}$$

$$y_{k+1} = y_k + u_{k+1} \tag{17}$$

Imagine a swarm of particles, each representing a potential solution to a problem. Each particle has a current location, a memory of its best location so far, and an awareness of the best location found by any particle in the swarm. These are analogous to:

- **u_k:** The particle's velocity, which determines how it moves through the search space.
- **P_{bestk}:** The best solution found by the particle itself.
- **y_k:** The particle's current location.
- **G_{bestk}:** The best solution found by any particle in the swarm.

Two factors influence how each particle moves:

Social-cognition factor (c2): This factor pulls the particle towards the best solution found by the swarm (Gbestk). It encourages the particles to explore promising regions of the search space together.

Self-cognition factor (c1): This factor pulls the particle towards its own best solution (Pbestk). It encourages the particles to continue to explore areas that have been successful for them individually.

Both c1 and c2 are values between 0 and 2, and they control the balance between these two influences. A higher c2 means the particles are more likely to follow the swarm, while a higher c1 means they are more likely to explore independently.

4.3 Hybrid Genetic Algorithm and Particle Swarm Optimization Approach:

This work proposes a hybrid optimization model combining Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) for parameter fitting, aiming to achieve a better balance between exploration and exploitation. The overall process is illustrated in Figure 1.

1. **Particle Swarm Optimization (PSO):**
   - Initialize a population of particles representing potential solutions.
   - Evaluate the fitness of each particle.
   - Update each particle's position based on its own best position ("P_{best}") and the swarm's best position ("G_{best}").
   - Generate a new generation of particles.
2. **Genetic Algorithm (GA) integration:**
   - Replace a portion of the newly generated PSO population with individuals selected based on their fitness (selection).
   - Introduce diversity by applying mutation and crossover operations to selected individuals.
3. **Repeat steps 1 and 2:**
   - Evaluate the fitness of the improved population.
   - Update P_{best} and G_{best}values.
   - Continue iterating until a stopping criterion is met.

This hybrid approach leverages the exploration strength of PSO and the exploitation power of GA, potentially leading to more efficient and effective parameter fitting.

5. Results and Discussions

Experimental Procedure:
The efficacy of our proposed algorithm was rigorously assessed on three representative test systems: IEEE 30-, 57-, and 118-bus systems. We benchmarked its performance against well-known methods like PSO and GA.

Performance Analysis:

Across three IEEE test systems (30-, 57-, and 118-bus), Tables 1, 2, and 3 showcase the proposed method's superior performance against conventional PSO and GA approaches for five objectives: fuel cost, voltage deviation, power losses, stability index (Lmax), and emissions. Our method consistently achieved the lowest cost, minimized voltage deviation for a more stable grid, reduced power losses for improved efficiency, lowered

Lmax for enhanced stability, and minimized emissions for environmental benefit. This demonstrates the proposed method's effectiveness in optimizing power systems while achieving significant economic and environmental advantages.

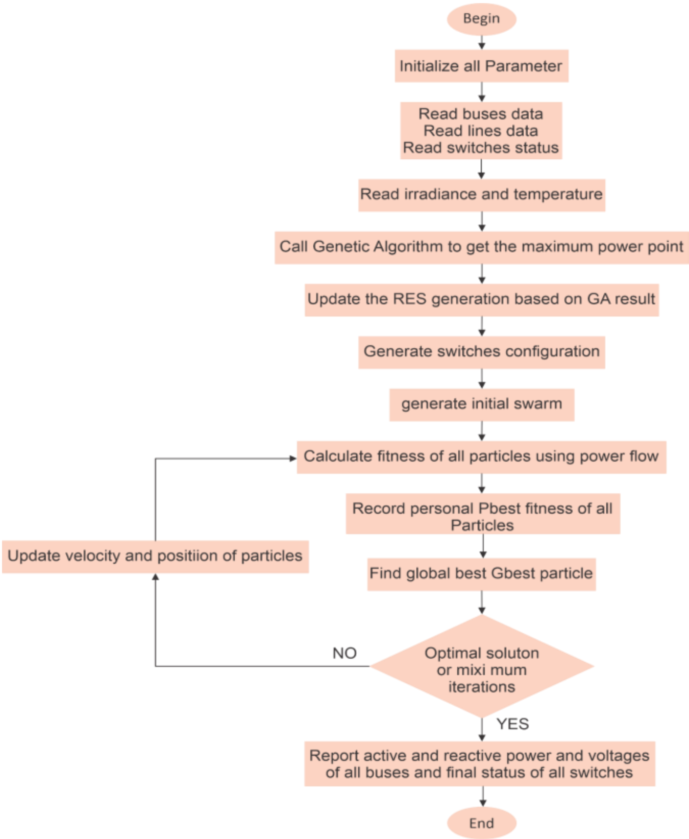

Fig 1: Reconfiguration of hybrid power networks PSO and GA

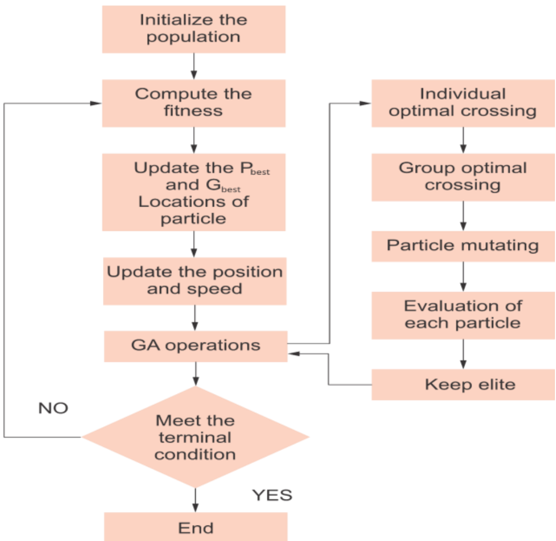

Fig 2: Process model of proposed Hybrid GA-PSO technique

Table 1: Performance analysis of proposed and conventional algorithms in IEEE 30 bus system

Methods	PSO	GA	PROPOSED METHOD
Fuel Cost (₹/hr)	799.41	601.24	596.96
VD	0.91	1.06	1.64
Ploss	6.776	9.26	6.602
Lmax	0.149	0.136	0.126
Emission (ton/hr)	0.466	0.469	0.466

Table 2: *Performance analysis of proposed and conventional algorithms in IEEE 57 bus system*

Methods	PSO	GA	PROPOSED METHOD
Fuel Cost (₹/hr)	830.2223	828.49	830.288
VD	4.488	4.922	4.484
Ploss	0.298	0.484	0.298
Lmax	0.243	0.284	0.242
Emission (ton/hr)	0.249	0.238	0.228

Table 3: *Performance analysis of proposed and conventional algorithms in IEEE 118 bus system*

Methods	PSO	GA	PROPOSED METHOD
Fuel Cost (₹/hr)	828.29	826.8471	827.78
VD	4.2768	4.622	4.262
Ploss	0.2978	0.44	0.266
Lmax	0.2401	0.261	0.246
Emission (ton/hr)	0.124	0.24	0.124

Conclusion

This work presents a novel hybrid optimization algorithm merging Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). Successfully applied to single and multi-objective optimization problems on the IEEE 30, 57, and 118-bus test systems, the method excels in exploring a wider search space for potential global optima. Compared to conventional approaches, it delivered superior performance across environmental, technical, and economic aspects, achieving significant reductions in fuel costs, voltage deviations, power losses, and emissions. Moreover, the proposed method showcases robustness against variations in population size and iterations, solidifying its effectiveness and versatility as a powerful tool for power system optimization.

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