Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Hybrid Intelligent Algorithm for Optimal Power Flow Enhancement with FACTS Devices

Dr Bikash Chandra Saha[0000-0003-2562-1594]1 Dr Avinash Kumar[0000-0001-7958-3744]2 Dr Abhishek Kumar3

[1] Associate Professor ,Deparetment of Electrical & Electronics Engineering ,Cambridge Institute of Technology,Ranchi-835103,Jharkhand,India

[2] Associate Professor ,Deparetment of Electrical & Electronics Engineering, RTC Institute of Technology,Ranchi, Jharkhand,India

[3] Assistant Professor ,Deparetment of Electrical & Electronics Engineering, RTC Institute of Technology,Ranchi, Jharkhand,India

bikash.eee@citranchi.ac.in

ARTICLE INFO

Received: 10 Sep 2023

Accepted: 30 Oct 2023

ABSTRACT

This study introduces a hybrid intelligent algorithm (HIA) that integrates particle swarm optimization (PSO) with chaos searching technique (CST) to address the optimal power flow (OPF) problem involving flexible alternating current transmission system (FACTS) devices. The proposed approach aims to enhance economic outcomes through the utilization of controllable FACTS devices. Specifically, the method evaluates two types of FACTS devices: thyristor-controlled series compensators (TCSC) and Static VAR Compensators (SVC). The OPF problem is divided into two distinct sub-problems; the first focuses on active power planning to minimize fuel costs, while the second addresses voltage deviations and reactive power violations through efficient reactive power planning involving multiple SVCs. The HIA employs a population-based algorithm that aggregates various solutions to identify the optimal outcome. To mitigate the limitations of PSO, particularly the extensive time and effort required for parameter tuning, CST is incorporated to enhance the diversity of the particle swarm, thereby preventing local optima entrapment. The HIA begins with a set of randomly initialized particles that navigate the search space. This optimization technique iteratively resolves the OPF by addressing the two sub-problems until convergence is achieved.

Keywords: Flexible AC Transmission System (FACTS); Hybrid Intelligent Algorithm (HIA); Optimal Power Flow (OFC), TCSC, SVC.

1 INTRODUCTION

The resolution of an Optimal Power Flow (OPF) problem identifies the most effective configurations for control variables within a power network while adhering to various constraints. Over the past four decades, the advancement of Flexible AC Transmission System (FACTS) [1] devices has enabled power systems to operate with greater flexibility, security, and cost-effectiveness. However, the integration of these FACTS devices has also introduced additional complexities into the operation of power systems. The Benders [2] decomposition method was initially introduced to address the optimal active power flow dispatch problem that includes FACTS devices, allowing for the representation of series compensators and phase shifters, although it did not account for specific line flow constraints. A subsequent approach based on decomposition was proposed to tackle the power flow control [3] problem with FACTS devices, yet it failed to merge the tilted OPF problem with the power flow control issue, potentially leading to suboptimal solutions. Additionally, a linear programming method for optimal power flow [4] was presented for enhancing power system network security. The modeling of FACTS devices for power flow studies and its significance in understanding their impact has also been discussed by Gotham and Heydt [5]. The presence of discrete control variables, such as switchable shunt devices, transformer tap positions, and phase shifters [6,7], adds further complexity to the solution process. Various global optimization techniques, including genetic algorithms (GA) [8], simulated annealing, tabu search (TS) [9], evolutionary programming, improved particle swarm optimization (IPSO)[10], and a novel crazy swarm optimization (NCSO) [11], have been explored. Furthermore, a simple genetic algorithm (GA) fuzzy system [12] and evolutionary programming have been applied

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to the OPF problem in large-scale power systems, while the Modified Bacterial Foraging Algorithm (MBFA) [13] has also been utilized for optimal power flow solutions in conjunction with FACTS device modelling. Author in [14] presents a particle swarm optimization (PSO) to solve the economic dispatch with consideration of many nonlinear characteristics of the generator, such as ramp rate limits, prohibited operating zones, and non-smooth cost functions. To overcome the drawbacks of the conventional methods related to the form of the cost function, and to reduce the computational time related to the large space search required by GA, this paper presents a HIA for the solution of large-scale OPF with practical generators constraints and with consideration shunt FACTS devices.

1.1 Contributions

The main contribution of the paper has been listed below:

- A dynamic modeling has been developed for IM using dq synchronously rotating reference frame.
- A Comparative analysis has been done under various condition such as phase loss and healthy condition.
- Utilized Ant Lion Optimization (ALO) algorithm to assess the feasibility, efficiency, and potential challenges associated with implementing a six-phase induction motor, ensuring optimal performance.

1.2. Organization of the paper

This document is organized as follows: Section 2 presents the methodology and the mathematical formulation of the OPF problem. Section 3 provides an overview of Particle Swarm Optimization (PSO) and introduces the Chaos Searching Technique (CST), along with a description of the proposed Hybrid Intelligent Algorithm (HIA). Section 4 discusses the numerical results, while Section 5 concludes the study with key findings and insights.

2. METHODOLOGY

2.1 Thyristor Controlled Series Compensator (TCSC) Modelling

When employing the DC network model, the representation of the transmission line incorporating the TCSC is illustrated in Fig.1. The overall susceptance of the transmission line can be expressed as follows:

$$\sigma_{pq} = \frac{1}{X_{pq} - X_p} \quad (1)$$

The power flow of the branch will be

$$P_{pq} = \sigma_{pq}\beta_{pq} \quad (2)$$

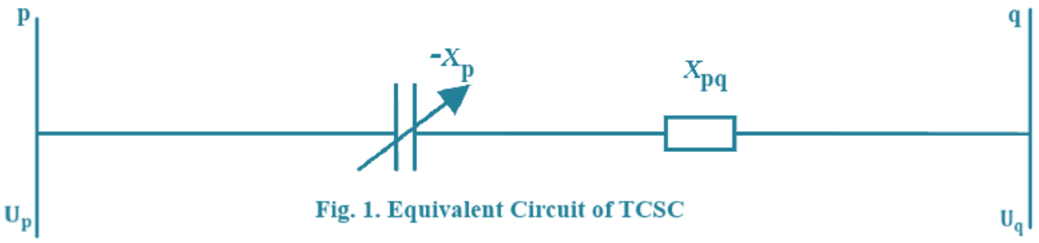

Fig. 1. Equivalent Circuit of TCSC

2.2. Static VAR Compensator (SVC) Modelling

The proposed steady-state model is utilized to integrate the Static VAR Compensator (SVC) into power flow analysis. This model conceptualizes the controller as variable impedance, predicated on an SVC arrangement that includes a fixed capacitor (FC) and a Thyristor-controlled reactor (TCR), as illustrated in Fig. 2. When a gate pulse is applied simultaneously to all thyristors within a thyristor valve, it initiates conduction through the valve. In the absence of firing signals, the valve will effectively block current near the zero crossing of the alternating current. Consequently, the Thyristor valve serves as the primary controlling component. The thyristors are activated symmetrically within a control angle range of 90 to 180 degrees relative to the voltage across the capacitor or inductor.

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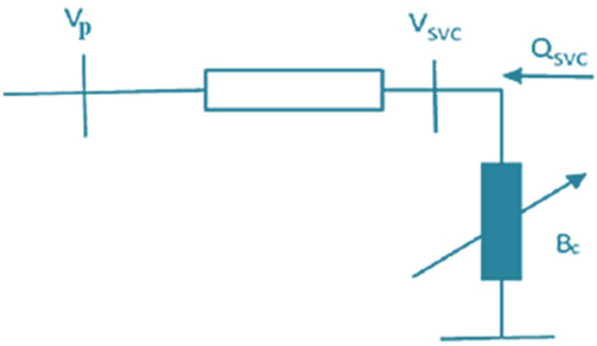

Fig. 2. SVC steady state circuit representation

$$V = V_p + X_L \quad (3)$$

The values of X_L fall within the range of 0.02 to 0.05 per unit relative to the SVC base. It is essential to establish a slope to prevent reaching operational limits. When the voltage limits are encountered, the SVC effectively behaves as a fixed reactance. The overall equivalent impedance of the SVC is X_e, can be expressed as follows:

$$X_e = X_C \frac{\pi/k}{\sin 2\gamma - 2\gamma + \pi(2 - 1/k)} \quad (4)$$

Where, $k = X_C/X_L$

2.3. Mathematical Formulation

In this study, concentrate on the optimal active power flow issue, utilizing the DC power flow model. When incorporating the n-1 security constraints, the optimal power flow problem can be articulated as follows:

To minimize CP,

$$\sum P_p = \sum L_p + P_l \quad (5)$$

$$H - \sigma S\beta = 0 \quad (6)$$

$$P \leq P \leq P'$$

$$H \leq H(0) \leq H'$$

$$H \leq H(l) \leq H'$$

where

C: Generation cost vector; P: Vector of active bus generation; se S: Transpose of bus branch incidence matrix; β:vector of angle across branch; σ: diagonal matrix of circuit susceptance; $H(0)$: vector of base state active power flow in lines; $H(l)$: vector of active power flow in lines when branch current is break out; P_l: Active power loss of system; L: active bus load vector; H and H': circuit flow limits; P and P': Generation limits;

The parameters of the FACTS devices can be adjusted in minute increments, with the newly introduced control variables regarded as continuous and constrained by defined lower and upper limits. Consequently, the reformulated optimal active power flow problem can be expressed in the following manner:

$$F_s = \sigma c(k_b \beta + \psi) \quad (7)$$

$$P \leq P_C \leq P'$$

$$-\psi \leq \psi \leq +\psi$$

where, k_b is the bus branch incidence matrix related to control line. While ψ is the vector of controlled line phase shifter angle and F_s is the specified line flow vector.P_C is the bus generation including the compensation injection power of phase shifter.

3. OPTIMIZATION TECHNIQUES

3.1 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is very well known and efficient optimization technique was inspired by the social behavior of animals such as fish schooling and bird flocking. The particle will then modify its direction such that it has additional components towards its own best position, p_{ibest} and towards the overall best position, g_{best}. The velocity updateequation is:

$$V_i^{(k+1)} = W \times V_i^k + c_1 \times r_1\left(p_{besti} - x_i^k\right) + c_2 \times r_2\left(g_{best} - x_i^k\right) \quad (8)$$

where x_i and V_i are the current position and velocity of particle i, respectively p_{besti} and g_{best} are the positions with the best objective value found so far by particle i and the entire population, respectively; W is the inertia weight factor; r_1 and r_2 are random variables in the range [0, 1]; c_1 and c_2 are acceleration constants; k is the number of iteration. The position update equation is:

$$x_i^{(k+1)} = x_i^k + V_i^{(k+1)} \quad (9)$$

3.2. Chaos Searching Technique (CST)

Chaos is a kind of non-periodic moving style which exists widely in the nonlinear system and is unique to the system. The chaos searching technique (CST) is a modern searching method [15]. CST has two steps: first one is to search all the points in turn within the changing range of variables and taking the better point as the current optimum point. Then it regards the current optimum point as the center. A tiny chaos disturbance is imposed and carefully searches to find out the optimum point. The chaos search technique has many advantages such as not sensitive to the initial value, easy to skip out of the locally minimum value, fast searchingvelocity and global gradual convergence. The following moreconvenient equation is used to generate the chaos sequence:

$$z_{i+1} = \aleph_i(1 - z_i) \quad (10)$$

where, $z_i \epsilon\ [0,1](i = 1, 2, \ldots)$and μ is the control parameter generated to replace that frog. The calculations then continue for a specific number of iterations.

3.3 Hybrid Intelligent Algorithm (HIA)

The basic idea of this new algorithm is to embed CST into PSO for solving the hydrothermal scheduling problems. The CST embedded in the PSO to improve the worse particles. CST also improves the diversity of the particle swarm to avoid PSO trapping the local optima. The upper level and lower level's decision variables are all randomly generated and updated by PSO or CST. Here the upper level's decision variable is encoding and the lower level's decision variable is computed according to the upper level's decision variable. The feasible weighting value is set up to replace the fitness value of the particle when it is infeasible, which can force the infeasible particle to be feasible. In the early stage of the algorithm, the feasible weighting value is used to rank the infeasible particles, which can avoid the situation that the infeasible particle is denoted as the best particle although it is the best of all when only the fitness value is used by all particles. The stepwise have to be taken:

1. At initial stage choose the parameters arbitrarily. Population size is set M =m+n, where m and n are the particles updated by PSO and CST respectably. Maximum velocity, V_{max}, two learning factors, c_1 and c_2, and two random variables, $r_1, r_2 \in [0, 1]$ are set. The maximum number of iterations (T) is initialized.
2. Randomly initialize each of the i^{th} (i = 1, 2..., M) particle randomly with initial position, X_i, within the pre-specified range and velocity, Vi, in the range of maximum speed, V_{max}. The best previously visited position of the i^{th} particle, i.e. $P_{i\,best}$, is initialized as X_i.
3. Evaluate the fitness values of the each particle of CST. If the solution exist the limit then the objective function value equals zero, and the particle is feasible. Then it add to the feasible list and set the upper level's

objective function value as the fitness value of the particle; otherwise, the particle is infeasible, and add the particle to the infeasible list.

4. Rank the particles. The particles, which are in the feasible list, are ranked in ascending order. Then, the other particles in the infeasible list are ranked in ascending order.

5. Update the local best position, P_{ibest}, and global best position, g_{best}. For the i^{th} particle, compare particle's fitness assessment with its P_{ibest}. If current value is better than P_{ibest}, then set the current value to P_{ibest}. Compare the first particle's fitness evaluation with the global best position, g_{best}. If current value is better than g_{best}, then set the current value to g_{best}.

6. Update the particles. For the first m particles, the velocity of particle and its new position will be assigned according to Eq. (8-9) and the n particles in the end of the list are updated using the CST with the initial chaos variable X_i.

7. Terminal conditions. t = t+1, If the number of iterations is larger than the maximum number of iterations (*T*), go to Step 8, otherwise go to Step 3.

8. Output the results. Output the optimal particle, compute and output the upper level and lower level's objective function values.

4. NUMERICAL RESULTS

The IEEE 30-Bus, 41-branch system was evaluated with voltage constraints set at lower and upper limits of 0.9 p.u. and 1.06 p.u., respectively, with the exception of PV buses where the maximum voltage is 1.1 p.u as shown in fig.3. The detailed input data for this system are taken from [13].To assess the effectiveness of the proposed method, a comparative analysis was conducted against other existing optimal power flow (OPF) algorithms. Reference [8] introduced a standard genetic algorithm (GA), while reference [12] explored an optimal power flow solution utilizing a GA-fuzzy system approach. Additionally, reference [13] presented a Modified Bacterial Foraging Algorithm (MBFA). The proposed method achieved an operating cost of 798.50 and a power loss of 8.2645, demonstrating superior performance compared to the methodologies documented in the literature. The results, as illustrated in Table 1, and in fig. 4 indicate that the proposed approach yields more favourable outcomes, with the optimal shunt compensation achieved at the standard load demand of 283.4 MW through reactive power planning, as referenced in [9,11]. Furthermore, the line flows obtained remain well within security limits when compared to other algorithms.

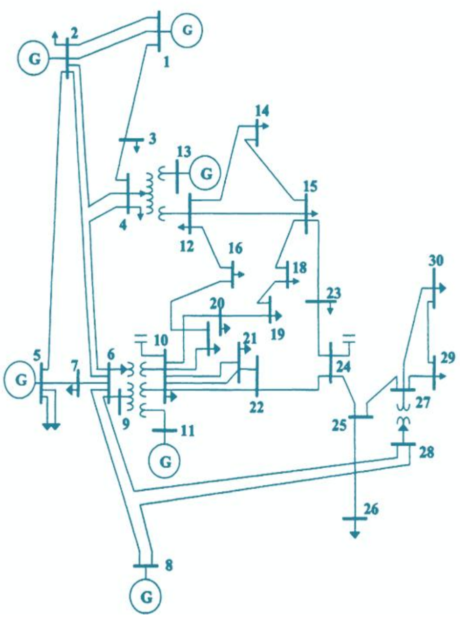

Fig. 3. IEEE 30 Bus system

Table1. Results of minimum cost and power generation with SGA, FGA and MBFA for IEEE 30 bus

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Sl. No.	Items	SGA [8]	FGA [12]	MBFA [13]	Proposed HIA
01.	**P1 (MW)**	179.367	175.137	164.501	**162.125**
02.	**P2 (MW)**	44.24	50.353	32.423	**31.725**
03.	**P5 (MW)**	24.61	21.451	21.459	**20.553**
04.	**P8 (MW)**	19.90	21.176	11.130	**15.423**
05.	**P11 (MW)**	10.71	12.667	23.872	**22.186**
06.	**P13 (MW)**	14.09	12.11	38.470	**31.054**
07.	**Q1 (MVAR)**	-3.156	-6.562	-3.609	**-2.924**
08.	**Q2 (MVAR)**	42.543	22.356	37.423	**36. 712**
09.	**Q5 (MVAR)**	26.292	30.372	24.985	**22.596**
10.	**Q8 (MVAR)**	22.786	18.890	19.530	**20.025**
11.	**Q11 (MVAR)**	29.923	21.737	15.821	**14.615**
12.	**Q13 (MVAR)**	32.346	22.635	7.598	**7.086**
13.	**θ1(deg)**	0.000	0.000	0.000	**0.000**
14.	**θ2(deg)**	-3.674	-3.608	-3.375	**-3.448**
15.	**θ5(deg)**	-10.141	-10.509	-9.596	**-9.125**
16.	**θ8(deg)**	-10.00	-8.154	-7.012	**-6.849**
17.	**θ11(deg)**	-8.851	-8.783	-4.789	**-4.253**
18.	**θ13(deg)**	-10.131	-10.280	-4.584	**-4.124**
19.	**P_{loss} (MW)**	9.5177	9.494	8.4625	**8.2645**
20.	**Cost ($/hr.)**	803.699	802.578	800.158	**798.50**

Initially, the overall real power loss within the system is determined to be 8.2645 MW when utilizing a shunt FACTS device. To enhance the reactive power planning efficiency of the system, the shunt FACTS device is strategically positioned at various locations. The optimization of power loss is achieved through the implementation of the HIA, which works in conjunction with enhancements to the bus voltage profile and the reactive power output of the generators. The convergence of the proposed HIA for OPF are shown in fig.5.

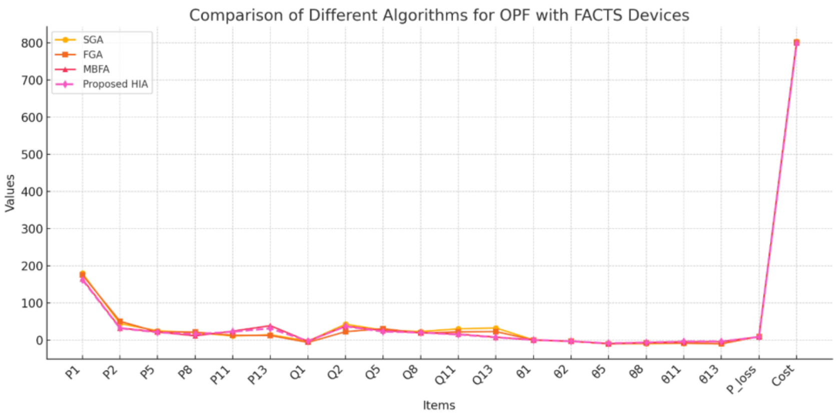

Fig. 4. Comparison of different algorithms for OPF with Facts Devices

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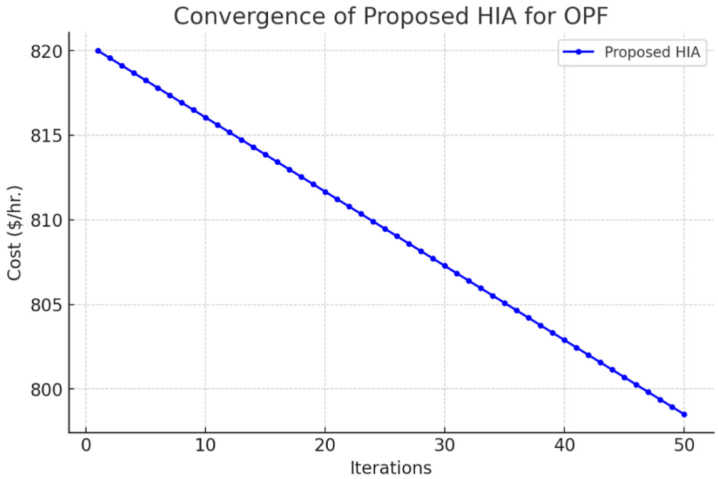

Fig. 5. Convergence of the proposed HIA for OPF

5. CONCLUSION AND FUTURE SCOPE

This paper introduces a Hybrid Intelligent Algorithm (HIA) designed to efficiently solve the large-scale Optimal Power Flow (OPF) problem while incorporating Flexible AC Transmission System (FACTS) devices. The proposed approach integrates Particle Swarm Optimization (PSO) with the Chaos Searching Technique (CST) to enhance optimization performance by improving search diversity and preventing premature convergence. Simulation results on the IEEE 30-bus system demonstrate that the HIA significantly reduces power loss (8.2645 MW) and operational cost ($798.50/hr.), outperforming conventional techniques such as Simple Genetic Algorithm (SGA), Fuzzy Genetic Algorithm (FGA), and Modified Bacterial Foraging Algorithm (MBFA). By decomposing the OPF problem into two iterative sub-problems—one focused on power flow control and the other on economic optimization—the proposed method ensures both cost-effectiveness and voltage stability, making it a promising solution for modern power system optimization.

The proposed Hybrid Intelligent Algorithm (HIA) can be scaled to large power networks beyond the IEEE 30-bus system, increasing its practicality for real-world applications. Future research can explore the integration of renewable energy sources, such as wind and solar, into the OPF framework to assess their impact on grid stability. Additionally, optimizing the real-time allocation and operation of FACTS devices can further enhance the efficiency and reliability of power system performance.

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