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Abstract. The increasing complexity of modern electric power systems (EPS) necessitates the development of intelligent optimization algorithms capable of ensuring reliable, economical, and stable system operation. Traditional analytical approaches, such as the incremental cost equality method, often face limitations when dealing with nonlinear, multi-parameter, and constrained optimization problems. These challenges highlight the need for more flexible and adaptive methods.This study explores the application of the Particle Swarm Optimization (PSO) algorithm — a heuristic optimization technique inspired by collective behavior in nature — for optimizing the operational states of electric power systems. The proposed PSO-based model incorporates adaptive control of inertia and acceleration parameters to improve convergence stability and prevent premature stagnation. A comparative analysis between the traditional incremental cost method and the PSO-based approach demonstrates the potential advantages of heuristic optimization in terms of flexibility, computational simplicity, and robustness. The results of this research indicate that PSO can be effectively applied to solve complex power system optimization problems, particularly under nonlinear and multi-constrained conditions. Furthermore, the adaptability of PSO provides opportunities for its integration into intelligent control and planning systems for short- and long-term operation of EPS.

INTRODUCTION

The rapid growth of electricity demand, depletion of natural resources, and intensifying environmental challenges have made the optimization of electric power system (EPS) operations increasingly important. Modern power systems are large-scale, interconnected, and complex networks in which electricity generation, transmission, and distribution processes must be managed efficiently while ensuring reliability, quality, and environmental sustainability [1, 14-17]. Therefore, one of the key tasks in power system operation is to determine the optimal operating conditions that minimize the total cost of electricity generation while maintaining compliance with technical and environmental constraints. Traditionally, optimization problems in EPS have been solved using classical analytical approaches such as the gradient method and the method of equal incremental cost. These methods have been widely used due to their mathematical simplicity and practical effectiveness in systems with well-defined and smooth objective functions. However, in real-world conditions, power systems are nonlinear, multi-modal, and subject to various uncertainties and discontinuities. The traditional methods assume continuity, differentiability, and the presence of a single global extremum in the objective function, which are rarely satisfied in practice. As a result, additional approximations and simplifications must be introduced, which lead to a reduction in accuracy and overall optimization efficiency [2-13, 18, 19].

In recent years, research attention has increasingly shifted toward heuristic and artificial intelligence–based optimization techniques, which offer promising alternatives for solving complex engineering problems. Heuristic algorithms such as Genetic Algorithms (GA), Evolutionary Programming (EP), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) have shown high adaptability, flexibility, and robustness in handling non-linear, non-differentiable, and multi-objective problems [5-7, 13, 18, 19]. These methods do not require gradient information and can explore large search spaces effectively, allowing for near-optimal solutions to be obtained with reasonable computational effort. Among them, the Particle Swarm Optimization (PSO) algorithm, inspired by the social behavior of bird flocks and fish schools, has attracted significant interest due to its simplicity, fast convergence, and strong global search capability. PSO has been successfully applied in various engineering domains, including load dispatch, network reconfiguration, and renewable energy integration [13].

This paper investigates the application of the PSO algorithm for optimizing the operating states of electric power systems. The proposed optimization approach is compared with the traditional equal incremental cost method, and the results demonstrate that PSO provides higher accuracy and efficiency in achieving optimal operation modes for modern complex power systems.

MATHEMATICAL MODEL AND OPTIMIZATION ALGORITHM

For any given time interval, the problem of optimizing the state of the electric power system can be formulated as follows:

-The cost function associated with the total fuel consumption of thermal power plants:

$$B = \sum_{i \in T} B_i(P_i) \to \min \tag{1}$$

-Boundary conditions for the active power balances in power system for the time interval:

$$W = \sum_{i \in T} P_i - P_L = 0, \tag{2}$$

- Boundary conditions for the permissible minimum and maximum active powers of the thermal power plants participating in the optimization:

$$P_i^{\min} \le P_i \le P_i^{\max}, \quad i \in T, \tag{3}$$

- Boundary conditions for the permissible maximum active power flows in controlled power transmission lines:

$$P_l \le P_l^{\max}, \quad l \in L_P. \tag{4}$$

It is required to determine the optimal values that ensure the minimization of the objective function while taking these constraints into account.

Where, T denotes the set of thermal power plants (TPPs) participating in the optimization process; L_P represents the set controlled power transmission lines; P_L- the total active load of the power system for the time interval under consideration, which includes the total power of consumers, the power of power plants not participating in the optimization, and the total losses in electrical networks..

Thus, in the presented model, power plants which are not participate in optimization, specifically solar and wind power plants, are considered based on their fixed capacities for the time interval under consideration. Hydroelectric power plants with reservoirs and specified water volumes for consumption during the control cycle are considered by classifying them as fictitious thermal power plants, as in [13].

Solving of the formulated problem using the method of relative increments involves for taking into account of functional constraints in the form of inequalities using the penalty function method. By applying the necessary condition for the extremum of the resulting generalized objective function, the problem is reduced to determining the power outputs of the thermal power plants (TPS) that satisfy the following condition [1]:

$$\begin{aligned} &b_1(P_1) + ш_1(P_1) = b_2(P_2) + ш_2(P_2) = \ldots = b_n(P_n) + ш_n(P_n), \\ &P_1 + P_2 + \ldots + P_n = P_н, \end{aligned} \tag{5}$$

Where $b_i(P_i) = \dfrac{\partial B_i(P_i)}{\partial P_i}$, $ш_i(P_i) = \dfrac{\partial Ш(P_i)}{\partial P_i}$, $Ш = \sum_{l \in L_P} Ш_l = \sum_{l \in L_P} \alpha \left(P_l - P_l^{\max}\right)^2$, $Ш_l$ - penalty function, which takes into account the constraint on permissible maximum power flow in lth controlled power transmission line.

From the above conditions, it follows that the influence of the boundary condition on the power output of the i-th plant can be taken into account by shifting its relative increment characteristic upward or downward. Thus, the computational process is carried out in an iterative manner, where at each step:

– the derivative of the objective function (1) is calculated for each power plant;

– the relative increment characteristics of the plants are reconstructed by adding the corresponding derivatives of the penalty function [12];

– the new power outputs for the next iteration are determined by optimally distributing the system load among the plants according to condition (5).

This iterative computation continues until all functional boundary conditions are satisfied. The quadratic form of the objective function used in this method is designed to account for equality-type boundary conditions, since the limiting function equals zero only when it reaches its boundary value. Therefore, when inequality-type boundary conditions are present, their satisfaction is verified after each iteration. If a boundary condition is met, the next step proceeds without considering it; otherwise, it is incorporated into the computation [4]. Hence, in addition to the limitations inherent to traditional methods described above, they are also characterized by difficulties in accounting for inequality-type functional boundary conditions. To overcome these drawbacks, the Particle Swarm Optimization (PSO) algorithm — one of the proposed heuristic methods — is employed to solve the power system state optimization problem. PSO is a heuristic optimization algorithm that models the natural movement behavior of a swarm of organisms. It was proposed by Kennedy and Eberhart in 1995 and has since been successfully applied to a wide range of optimization problems [2-3, 9]. The main idea is that a group of particles explores the search space collectively to find the best solution. The algorithm is inspired by the cooperative food-searching strategies of animals such as flocks of birds or schools of fish. Each particle moves within the permissible region and, after each movement, communicates its current best position to other neighboring particles or to several members of the swarm. As a result, each particle determines its next optimal step based on the paths previously explored by others. When all particles update their current positions, the next iteration of the search process explores a region closer to the global optimum of the objective function. As this process continues, the entire swarm gradually converges toward the optimal solution of the objective function. To illustrate the operation of this algorithm, consider minimizing the following function with respect to the unknowns $x_1, x_2, \ldots, x_n$ within the domain bounded by their permissible minimum and maximum values [11]:

$$F(x_1, x_2, \ldots, x_n) \to \min\ , \tag{6}$$

$$x_{j.\min} \le x_j \le x_{j,\max}, \quad j = 1, 2, \ldots, n\ . \tag{7}$$

In this case, each particle i in the swarm is n-dimensional, and its state is determined by the corresponding values of the unknown variables $x_1, x_2, \ldots, x_n$.

1. Initialization of particle positions.The initial positions of the particles are generated first. The swarm size (i.e., the number of particles) is denoted by m, and for each particle i, the initial values of the unknown variables are assigned within the permissible region defined by condition

$$x_{ij}^{(0)}, \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n\ . \tag{8}$$

2. Velocity (step size) determination.Each particle searches for the optimal position within the allowable region by moving with a certain velocity (or step size). The value of this velocity (step) is randomly chosen for each particle (and for each of its components) in such a way that condition (8) is not violated [8]:

$$v_{ij}^{(0)}, \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \tag{9}$$

3. Fitness evaluation. The fitness (or suitability) of each particle is evaluated based on the objective function values computed at their previous $(t-1)$-th iteration positions (or, for the first iteration, at their initially assigned positions). By calculating the corresponding objective function values $F_{ij}^{(t-1)} = F\left(x_{ij}^{(t-1)}\right)$, each particle's individual best position $F_{ij.Pbest}^{(t-1)} = F\left(x_{ij.Pbest}^{(t-1)}\right)$is determined. Then, among all particles' individual best positions, the global best position of the entire swarm $F_{j.Gbest}^{(0)} = F\left(x_{j.Gbest}^{(0)}\right)$ is identified [3].

4. Velocity update and position adjustment. In every subsequent iteration, the velocity and position of each particle (i.e., the updated values of the unknown variables for the next iteration) are recalculated according to the following expressions: $x_{ij}^{(t)} = x_{ij}^{(t-1)} + v_{ij}^{(t)}, \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n$

In this case, the new velocity values at the current iteration are determined as follows:

$$v_{ij}^{(t)} = \omega v_{ij}^{(t-1)} + c_1 r_{1ij}^{(t)} \cdot \left(x_{ij.best}^{(t-1)} - x_{ij}^{(t-1)}\right) + c_2 r_{2ij}^{(t)} \cdot \left(x_{j.Gbest}^{(t-1)} - x_{ij}^{(t-1)}\right), \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \tag{10}$$

Where, $\omega v_{ij}^{(t-1)}$ represents the inertial component (sometimes referred to as the flight direction), which prevents abrupt changes in the particle's trajectory and ensures a smooth motion by preserving part of its previous direction;

ω is the inertia weight, whose value is typically chosen within the range of 0.5–1.0; $c_1 r_{1ij}^{(t)} \cdot \left(x_{ij.best}^{(t-1)} - x_{ij}^{(t-1)}\right)$ denotes the cognitive component, which reflects the particle's memory of its own previously found best position;

$c_2 r_{2ij}^{(t)} \cdot \left(x_{j.Gbest}^{(t-1)} - x_{ij}^{(t-1)} \right)$ represents the social component, which characterizes the current performance associated with the globally best position found by the swarm; c_1, c_2 are positive constants, referred to as acceleration coefficients, which control the tendency of particles to move toward their individual and global best positions;

and $r_{1ij}^{(t)}, r_{2.ij}^{(t)}$ are uniformly distributed random numbers in the interval [0, 1], introduced to maintain the diversity of the swarm [1, 5]. This iterative computational process continues until the termination condition of the algorithm is satisfied.

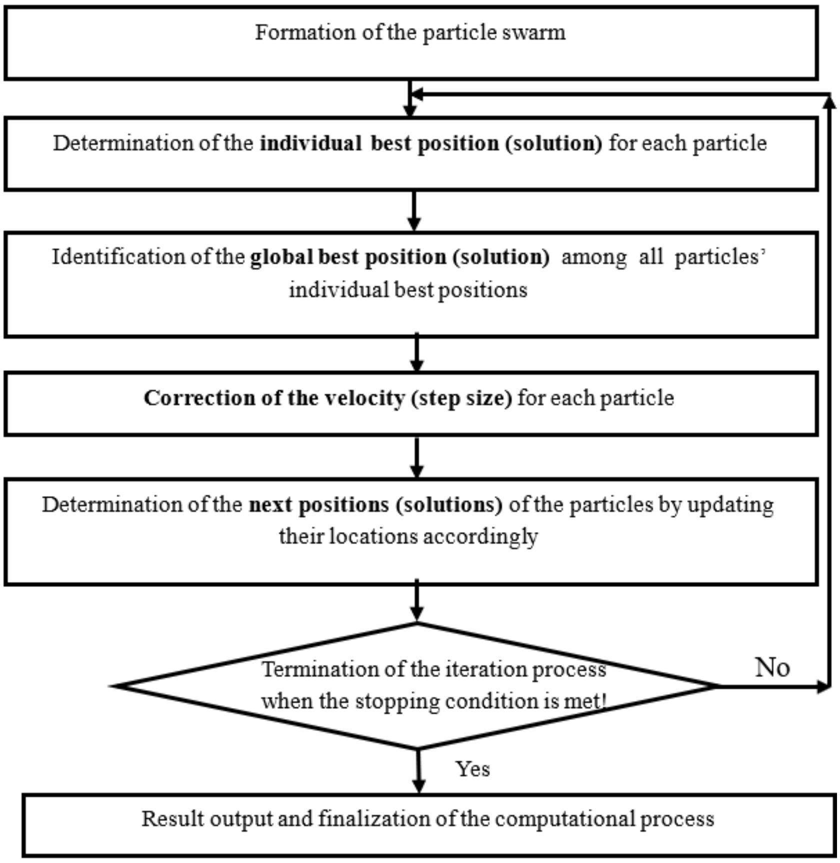

FIGURE. 1. An enlarged block diagram of the PSO optimization algorithm.

Figure 1 illustrates the enlarged block diagram of the Particle Swarm Optimization (PSO) algorithm. The process begins with the initialization of a particle swarm, where each particle represents a potential solution to the optimization problem. During each iteration, the individual best position of every particle is determined and compared to identify the global best position within the swarm. Based on these positions, the velocity and location of each particle are updated iteratively to explore the search space effectively. The algorithm continues until a predefined stopping criterion is satisfied, at which point the final optimal solution is obtained. This iterative mechanism enables PSO to achieve efficient convergence toward the global optimum with minimal computational complexity. If this condition is not satisfied, each subsequent iteration is performed starting from step 3. As a termination criterion for the iterative computational process, either a predefined number of iterations or a slowdown in the change of the objective function value can be adopted [20].

RESEARCH RESULTS

The presented model of power system state optimization based on the PSO algorithm, as well as the efficiency scheme of the solution algorithm, has been investigated using an example of power system state optimization shown in Figure 2. Thermal power plants (TPS) are located at nodes 0, 1, 6, and 7, and they are characterized by the following quadratic fuel consumption functions (t.e.f./h):

$B_1 = 4,7 + 0,304 P_1 + 0.00067 P_1^2$; $B_6 = 4.83 + 0.296 P_6 + 0.00079 P_6^2$;

$B_7 = 6.34 + 0,3 P_7 + 0.00022 P_7^2$; $B_8 = 4.67 + 0.292 P_8 + 0.00065 P_8^2$;

The power outputs of all thermal power plants (TPS) can vary within the following ranges:

$50\ MW \le P_i \le 250\ MW$

Nodes 2, 3, 4, and 5 are load nodes, and their power demands are as follows:

P_2=100 MW, P_3=120 MW, P_4=95 MW, P_5=105 MW.

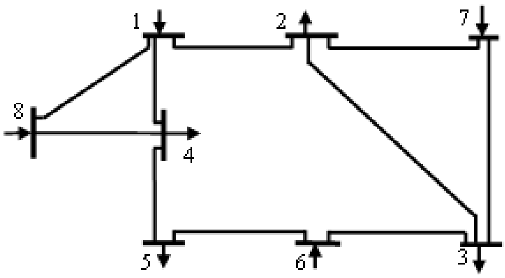

FIGURE. 2. 8-node test circuit

For the above 8-node test scheme, to evaluate the effectiveness of power system state optimization, the problem was first solved using the traditional method of relative increment equations, and the corresponding results were obtained (Table 1).

TABLE 1. Results of optimization of the state of EPS by the method of equality of relative growths

TPP, *i*	P_i , MW	B, (t.e.f./h)
1	66.95	28.0559
6	61.84	25.705
7	212.97	80.209
8	78.24	31.495
Total	**420**	**165.4649**

The results obtained using the PSO algorithm are presented in Table 2.

TABLE 2. Results of optimizing the state of EPS using PSO algorithm methods.

TPP, *i*	P_i , MW	B, (t.e.f./h)
1	66.947	28.0547
6	61.841	25.706
7	212.974	80.210
8	78.238	31.494
Total	**420**	**165.4647**

A comparison of the results presented in Tables 1 and 2 shows that they are identical. This demonstrates the high accuracy of the applied PSO algorithm. The obtained results confirm that this algorithm is capable of efficiently solving optimization problems with multi-extremal and discontinuous objective functions while taking into account limiting constraints. In this study, a comparative analysis of the traditional method of relative increment equations and the modern Particle Swarm Optimization (PSO) algorithm was carried out to optimize the states of electric power systems (EPS). The research results show that each method possesses its own advantages and limitations, which depend on the specific conditions and requirements of power system optimization. Using the traditional method of relative increment equations, the total fuel consumption was found to be 165.4649 t.e.f./h. The main drawback of this method lies in the difficulty of accounting for functional boundary constraints and its limited capability to find the global optimal solution in multi-parameter and complex problems. Therefore, this method is mainly applied for approximate analyses of power system states and has restrictions in terms of accuracy and efficiency under real operating conditions [11]. In contrast, the proposed PSO algorithm features a simpler computational process and achieved a total fuel consumption of 165.4647 t.e.f./h**.** The adaptive control of the inertia coefficient and other parameters enhances the efficiency of the PSO algorithm. This method has the advantage of avoiding entrapment in local minima, making it highly suitable for complex, multi-parameter systems. Moreover, the flexibility and robustness of the PSO algorithm enable its effective application in optimizing both short-term and long-term operating states of electric power systems. Furthermore, the rational selection of algorithm parameters and their adaptation to specific EPS problems can significantly improve the optimization performance. Proper tuning of the inertia coefficient, acceleration coefficients, and the number of iterations contributes to achieving higher optimization efficiency. Future research on the practical implementation and hybridization of such heuristic algorithms is expected to open promising prospects for optimizing the operational states of electric power systems.

CONCLUSIONS

1. Optimization algorithms for the states of electric power systems (EPS) based on heuristic methods, particularly the Particle Swarm Optimization (PSO) approach, were developed and their effectiveness was investigated.
2. The study of the efficiency of EPS state optimization algorithms based on the heuristic PSO method demonstrated that several limitations inherent to traditional approaches can be effectively eliminated.
3. It was shown that optimization algorithms based on the PSO method can be successfully applied for planning and controlling complex EPS operating conditions while taking various boundary constraints into account.

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