

Performance Evaluation of PSO, GA, DOA, NRBO, and GGO for Static Optimal Power Flow: A Benchmarking Study

Alper Buğra Polat^{1*} , Osman Altay² 

¹ Bandırma Onyedi Eylül University, Department of Software Engineering, 10300 Bandırma, Türkiye.

² Manisa Celal Bayar University, Department of Software Engineering, 45400 Manisa, Türkiye.

*alperpolat@bandirma.edu.tr

* Orcid No: 0009-0000-0572-3054

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Abstract

The growing demand and power of modern power systems necessitates an economical and stable operation, and therefore, the Optimal Power Flow (OPF) problem is of heavy research interest. The OPF must be solved efficiently to lower operational costs and ensure system stability. A comprehensive comparative study in this paper compares the performance of five metaheuristic algorithms for solving the fuel cost minimization problem of the OPF problem. Two well-known algorithms, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), and three new ones, Dream Optimization Algorithm (DOA), Newton-Raphson-Based Optimizer (NRBO), and Greylag Goose Optimization (GGO), were tested on the benchmark IEEE 6-bus, 30-bus, and 57-bus systems. The performance of the algorithms was compared in terms of statistical measures of the best cost, mean cost, and standard deviation from ten independent runs. Numerical findings indicate that the performance of algorithms is highly dependent on system size. For the 6-bus case, NRBO had the lowest fuel cost, while PSO had better stability with the lowest standard deviation. In the 30-bus case, NRBO was the most effective algorithm to utilize, having better performance in all aspects measured. In the larger 57-bus system, PSO had the best solution overall but least consistent in performance. This study concludes that there isn't a single best algorithm for all OPF problem sizes, providing an authoritative benchmark that marks the strengths and weaknesses of classical and contemporary metaheuristics across different power system applications.

Keywords: Metaheuristic, Optimal Power Flow, Optimization, Fuel Cost

1. Introduction

The continuously increasing population worldwide and technological developments have created more electricity demand, resulting in more efficient power systems [1]. The Optimal Power Flow (OPF) problem forms the basis for the analysis needed to make the power system safer and more efficient [2]. OPF offers the capability of pre-tuning operating states of the power system based on an objective given. The OPF problem can be used for various purposes, i.e., minimizing the fuel cost, reducing the loss of transmission lines, optimizing the unit emissions of the generators, and voltage deviation analysis [3].

There have been decades of research in OPF, the earliest of which was conducted by Carpentier in 1962 [4]. Today, the OPF problem can be solved using many conventional techniques, such as the gradient method,

Newton's method, sequential linear programming, sequential quadratic programming, linear and nonlinear interior-point methods, and semi-definite programming [5]. The OPF problem can be formulated mathematically with constraints and objective functions. Metaheuristic optimization algorithms can be used to create solutions for the OPF problem [6].

There are numerous metaheuristic algorithms present today. These methods are designed using different techniques such that they do not get stuck in the phase of exploration and exploitation. The "no-free lunch" theorem illustrates that there is no single method to find the optimum solution for all problems [7]. These methods have come to be used in solving many problems in industry, business, and engineering nowadays. Algorithms are designed with motivation from fields as diverse as physics and mathematics to biology, social behavior, sports, and music [8]. Unlike traditional algorithms, the metaheuristic algorithms do

not require very strict limitations on the mathematical formulation of the optimization problem and do not require the objective function to be continuous and differentiable. They are effective in finding the global optimum [9]. These characteristics make them good solution algorithms for the OPF problem.

For this research, the aim is to find the solution to the minimum fuel cost objective function of Institute of Electrical and Electronics Engineers (IEEE) standard 6-bus, 30-bus, and 57-bus systems for the OPF problem by employing two commonly used and three newly suggested and most often preferred metaheuristic optimization algorithms. MATPOWER solved the 6-bus and 57-bus systems. The Newton-Raphson (NR) method has been used for the solution of the 30-bus system. Conventional algorithms are Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), while recently developed and popular algorithms are Dream Optimization Algorithm (DOA), Newton-Raphson Based Optimizer (NRBO), and Grey Wolf Optimizer (GWO).

Contributions of this study: a comprehensive comparative analysis of two traditional (PSO, GA) and three novel metaheuristic algorithms (DOA, NRBO, GGO) is conducted for the OPF problem. Their performance is strictly compared on small, medium, and large-scale standard IEEE test systems (6-bus, 30-bus, and 57-bus) under an identical experimental environment to make an unbiased comparison. The work empirically demonstrates that the performance of metaheuristic algorithms for the OPF problem is highly scale-dependent, and it offers critical insights into algorithm selection for practical power system applications. Exhaustive statistical analysis, including convergence behavior and result distribution, is provided, demonstrating solution quality vs. stability trade-offs for each of the algorithms.

Following the introduction, the second section of this research introduces and explains the OPF problem, the objective function equations to be used, and the meaning of the variables. The third section presents a detailed explanation of the metaheuristic optimization methods used. A comparison of the performances of the metaheuristic methods used is presented in the fourth section. For purposes of comparison, statistical analysis has been done based on the optimal results of ten independent runs in the same conditions. The fifth and final section presents the results and recommendations based on the analyses. The purpose of this research is to determine solutions to the OPF problem using classical and contemporary metaheuristic optimization methods and compare their performance.

2. Optimal Power Flow

OPF is a nonlinear, complex optimization problem. The OPF problem has various equality and inequality constraints of power system operating and stability. The mathematical model of the OPF problem, along with its constraints, is given below [10].

$$\text{Objective Function} = \min f(x, u) \quad (2.1)$$

$$\text{Equality Constraints} = g(x, u) = 0 \quad (2.2)$$

$$\text{Inequality Constraints} = h(x, u) \leq 0 \quad (2.3)$$

Here, $f(x, u)$ is the objective function. x is the dependent variable, and u is the independent variable. $g(x, u) = 0$ and $h(x, u) \leq 0$ are the equality and inequality constraints, respectively. The objective function is given below for minimization of total fuel cost quadratically for all generators.

$$\begin{array}{ll} \text{Objective} & \text{Function:} \\ \min F = \sum_{i=1}^{N_G} (a_i P_{g_i}^2 + b_i P_{g_i} + c_i) & (2.4) \end{array}$$

Quadratic fuel cost models represent a generator's fuel consumption as a quadratic function of its output power. Here, N_G represents the number of generators, P_{g_i} is the active power generation of the i -th generator, and a_i , b_i , and c_i are the second-degree, first-degree, and fuel cost constant coefficients, respectively. When the fuel cost function is linear, a_i will be zero, and b_i will represent the marginal increasing cost of the i -th generator, while c_i will represent the minimum no-load fuel cost. The objective function and the constraints in the form of alternating current (AC) power flow are solved by using appropriate values. The AC power flow equations are as given below, with equations 2.5 and 2.6.

$$P_{g_i} - P_{d_i} = V_i \sum_k V_k [G_{ik} \cos(\theta_i - \theta_k) + B_{ik} \sin(\theta_i - \theta_k)] \quad (2.5)$$

$$Q_{g_i} - Q_{d_i} = V_i \sum_k V_k [G_{ik} \sin(\theta_i - \theta_k) - B_{ik} \cos(\theta_i - \theta_k)] \quad (2.6)$$

P_{d_i} and Q_{d_i} are the active and reactive power loads at the i -th bus, respectively. V_i and V_j are the magnitudes of voltage at buses i and j , respectively. θ_i and θ_j are the phase angle voltages at buses i and j , respectively. G_{ik} and B_{ik} are Y-bus admittance matrix elements. Mathematical formulations of equality constraints are given below.

$$P_{g_i}^{\min} \leq P_{g_i} \leq P_{g_i}^{\max} \quad (2.7)$$

$$V_j^{\min} \leq V_j \leq V_j^{\max} \quad (2.8)$$

$$Q_{g_i}^{\min} \leq Q_{g_i} \leq Q_{g_i}^{\max} \quad (2.9)$$

$$T_l^{\min} \leq T_l \leq T_l^{\max} \quad (2.10)$$

$$QC_m^{\min} \leq QC_m \leq QC_m^{\max} \quad (2.11)$$

Equation 2.7 is applied to the limits of the active powers of the generators. Equation 2.8 is applied to the transformer voltage limits. Equation 2.9 is applied for the reactive power limits. Equation 2.10 is applied to specify the transformer tap ratio limits. Equation 2.11 is applied for the reactive power compensator limits [11].

MATPOWER was used in solving the 6-bus and 57-bus systems in accordance with the IEEE standard. MATPOWER is a complete and out-of-the-box power system analysis tool. It is possible to directly solve the OPF problem by using OPF and equality, and inequality constraints. In the case of the 30-bus system, the Newton-Raphson method was used. The Jacobian matrix with all of the constraints' derivatives and equalities' expressions was recomputed in every iteration. NR-based solutions mostly use an iterative technique to find the optimum point. The 6-bus, 30-bus, and 57-bus systems, according to IEEE standards are dealt with in depth in Figure 1, Figure 2, and Figure 3 presented below.

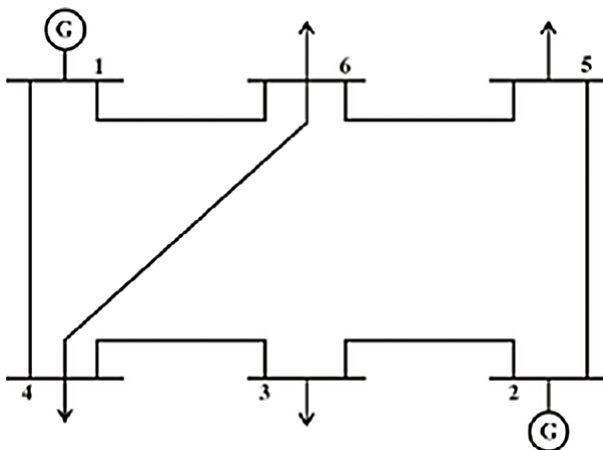


Figure 1. 6-bus Test System Diagram [12]

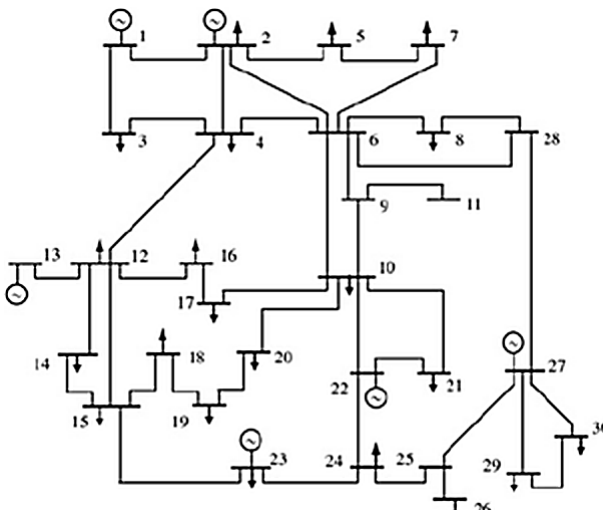


Figure 2. 30-bus Test System Diagram [13]

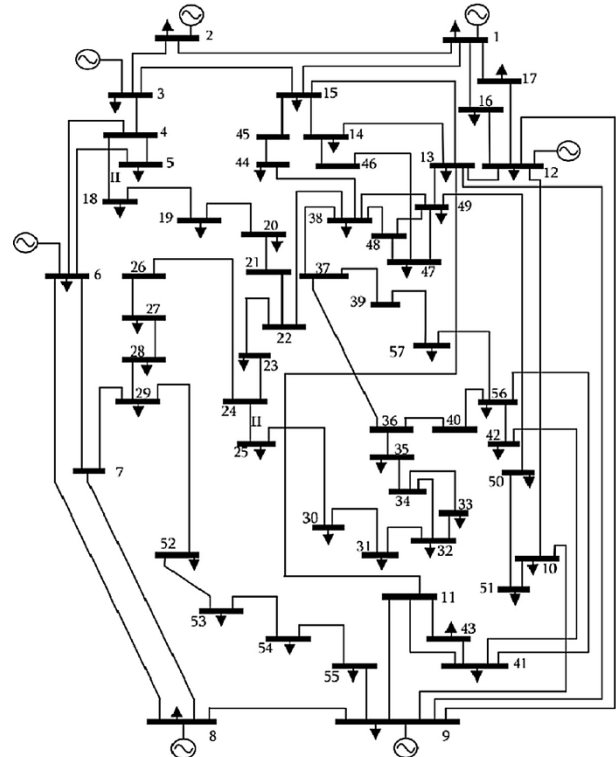


Figure 3. 57-bus Test System Diagram [14]

3. Metaheuristic Methods

Metaheuristic approaches are categorized into 11 types, but can be explained under 5 broad headings. The headings can be identified as physics-based, swarm-based, evolution-based, human-based, and game-based [15]. Approaches defined by being inspired by animal group movements are known as swarm-based approaches. There are numerous swarm-based approaches these days. Some of the swarm-based methods are Northern Goshawk Optimization (NGO) [16], Tuna Swarm Optimization (TSO) [17], Cat and Mouse Based Optimizer (CMBO) [18], and Swallow Swarm Optimization (SSO) [19]. Evolution-based methods are designed based on inspiration from biological concepts such as evolution and genetics. Some of them are Partial Reinforcement Optimizer (PRO) [20], Tree Growth Optimization (TGO) [21], and Differential Evolution Algorithm (DEA) [22]. Optimization methods developed based on the realization of physics laws and what is observed in the physical world are called physics-based methods. Big Bang–Big Crunch (BBBC) [23], Archimedes Optimization Algorithm (AOA) [24], Multi-Verse Optimizer (MVO) [25], and Thermal Exchange Optimization (TEO) [26] are a few examples of physics-based optimization methods. Methods developed based on learning from the nature of human beings are called human-based methods. They are designed by getting inspiration from processes such as human social interactions, learning bases, and brain functions. Teaching-Learning-Based Optimization (TLBO) [27], Human Mental Search (HMS) [28], and Brain Storm

Optimization Algorithm (BSOA) [29] are a few of them. Game-based optimization methods are developed with inspiration from game players and rules. Football Game Optimization (FGO) [30], Team Game Optimization (TGO) [31], and Dart Game Optimization (DGO) [32] could be referred to as examples of approaches based on games.

Ongoing endeavors to seek greater and more effective solutions to the OPF issue have witnessed a number of new metaheuristic algorithms. As an example, recent attempts have been inclined to be fascinated by some new bio-inspired algorithm; for instance, Circulatory System-Based Optimization (CSBO) has been utilized for minimizing fuel costs on benchmark IEEE standard test systems [33]. Aside from nature-inspired, some other studies have come up with the algorithm, for instance, Manta Ray Foraging Optimization (MRFO), which is utilized to resolve multi-objective issues of OPF nature [34].

One other significant trend within recent literature is the focus on more complex, non-standard power systems, specifically hybrid AC/DC grids. In trying to surmount the challenge of said systems, enhanced or specialized algorithms have been put forward, e.g., an Improved Phasor Particle Swarm Optimization (IPPSO) with specific application to hybrid AC/DC grids [35]. For multi-objective OPF problems of these hybrid networks, new algorithms like the Multi-Objective Grasshopper Optimization Algorithm (MOGOA) [36] and a dynamic switched crowding-based multi-objective PSO [37] have been proposed. The issue also extends to the mathematical formulation itself, with new OPF models being developed for the efficient operation of hybrid power networks [38]. Furthermore, the complexity is increased with the introduction of new technologies like VSC-MTDC transmission lines and renewables, which have been a subject of interest for recent OPF studies [39]. Even for traditional AC systems, the development of new isolated algorithms like the Artificial Rabbits Optimization (ARO) is an open research issue [40].

The table below shows the studies and focus points of the studies on the OPF problem in the recent literature.

Table 1. Summary of Recent Literature for the OPF Problem

Reference Number	Algorithm(s) Used	Key Focus / Objective(s)	Gap Addressed by Our Study
[40]	Artificial Rabbits Optimization	Standard AC Systems	Introduces and evaluates a single novel algorithm, highlighting the need for broader comparisons against other new methods.
[33]	Circulatory System-Based Optimization	Standard AC Systems	Proposes another novel bio-inspired algorithm, further emphasizing the trend of new methods requiring systematic
[35]	Improved Phasor Particle Swarm Optimization	Hybrid AC/DC Power Grids	benchmarking. Focuses on a specialized system type (AC/DC) and improves a specific algorithm (PSO) for that niche.
[34]	Manta Ray Foraging Optimization	Standard AC Systems	Applies another recently proposed standalone algorithm, but does not provide a scalability analysis across different system sizes.
[36]	Multi-Objective Grasshopper Optimization Algorithm	Hybrid AC/DC with Multi-Objective OPF	Addresses a complex problem (multi-objective OPF) on a specialized grid, not the foundational static problem.
[38]	Mathematical Modeling	Hybrid AC/DC Network Modeling	Focuses on the mathematical formulation of hybrid networks rather than a comparative evaluation of metaheuristic solvers.
[39]	Particle Swarm Optimization (PSO)	Hybrid AC/DC with VSC-MTDC	Applies a classic algorithm to a very specific and advanced topology (VSC-MTDC), not a general benchmark.
[37]	Advanced Multi-Objective PSO (DS-CMOPSO)	Hybrid AC/DC with Multi-objective OPF	Proposes a highly specialized evolutionary algorithm for a complex problem on a non-standard grid.
This Study	PSO, GA, DOA, NRBO, GGO	Standard AC Grids	Provides a systematic benchmark of recent vs. classic standalone algorithms on foundational AC systems, analyzing performance, stability, and scalability across small, medium, and large scales.

3.1 Particle Swarm Optimization

PSO is a metaheuristic optimization algorithm developed under the banner of swarm intelligence. In PSO methodology, candidate solutions are constructed with the help of a swarm comprising individuals named particles. Particles update their position and velocity to move to the best position they find for themselves, and at the same time, move towards the position of the individual with the best performance in the swarm. PSO is a powerful and widely used method due to its small number of adjustable parameters, simple implementation steps, and strong balance between local and global search [41].

3.2 Genetic Algorithm

GA is a metaheuristic algorithm based on the evolutionary process. Candidate solutions in the GA method are represented as individuals. Individuals are

developed through generations by crossover, selection, and mutation operations. Good fitness individuals are chosen during selection and carried forward to the next generation. New combinations are produced by crossover, while genetic diversity is created by mutation. The GA algorithm can converge to the global optimum in large search spaces, can be executed in parallel processes, and can be utilized efficiently for constrained problems. All these features make it a widely applied metaheuristic method [42].

3.3 Dream Optimization Algorithm

DOA is a metaheuristic optimization algorithm that adopting an idea from human awareness and the common nature of dreams. Utilizing properties of memory retention, partial forgetting, and self-organization existing in dreams, memory strategy, forgetting, and complementary strategy, and dream-sharing strategy have been proposed. Optimization is divided into exploration and exploitation stages and produces efficient optimization outcomes. The optimization ability of the DOA method in locating robust global optima and evading local minima, its ratio of exploration and exploitation phases, its history of search, as well as population diversity, are all attained through its special search mechanism. It was formulated on the basis of brain activity fluctuations during sleep and the reasons for dreaming. With the conversion of the characteristic aware state and information process mechanism of dreams into mathematical models, optimization problems can be efficiently solved using the ensuing method [43].

For application in the OPF problem context, the Dream Optimization Algorithm is specifically designed as follows. Each candidate solution in the population, or a 'dream,' corresponds to a vector of control variables. The vector includes active power dispatches of dispatchable generators, generator bus voltage setpoints, transformer tap ratings, and reactive power injections from shunt compensators. The fitness of all solutions is calculated by calculating the total fuel cost as shown by the objective function in Equation (2.4). In order to consider the operating constraints of the power system, a static penalty function strategy is employed. Every other solution vector not in the equality or inequality constraints of the system (e.g., generator limits, voltage limits, or line flows) is penalized by adding a large number to its objective function cost. This way, DOA's search process will naturally be guided automatically to the feasible space in the solution space, and thus the ultimate optimal solution is not only low-cost but operationally feasible as well.

3.4 Newton-Raphson-Based Optimizer

NRBO is a metaheuristic approach derived from physics. Its working mechanism is aimed at overcoming

slowness in operation as well as local minima trapping of conventional optimization algorithms. Its development involves the use of the root-finding method of the Newton-Raphson mathematical equation. The NRBO algorithm starts finding an optimal solution by initializing random starting points within the boundaries of candidate solutions. NRSR is used in the development of the algorithm. During initial setup, NRSR controls the vectors and therefore ensures precise exploration of the feasible space. NRSR is implemented in the model to accelerate the Newton-Raphson method and improve its inclinations. It is also believed that some adjustment is conceivable in this approach, such that it can attain accurate solutions within the search area. Because of this, some adjustments have been made in this algorithm. Some additional approaches have been developed for balancing the exploration phase and the exploitation phase. The exploitation phase has been altered with parameters such that this algorithm can carry out exploitation in the right direction. The direction-finding strategy revolves around the exploitation phase. Different mathematical formulas are utilized in local and global searches [44].

For application to the OPF problem, the NRBO maximizes a specified set of power system variables. Each 'search agent' of the NRBO population is a prospective solution vector consisting of the control variables: generator active power outputs, generator bus voltages, transformer tap positions, and shunt compensator outputs. The objective function, on which NRBO minimizes, is the total fuel cost calculated according to Equation (2.4). To ensure the solutions fit within the physical and operational limitations of the power system, a penalty function is embedded within the fitness function. When a candidate solution violates any of the constraints designed, a high penalty value is appended to its calculated fuel cost. This penalty mechanism forces the NRBO's search operators to discard infeasible solutions and converge towards an optimal and feasible operating point of the power system.

3.5 Greylag Goose Optimization

GGO is an animal-inspired metaheuristic algorithm. GGO tackles difficult optimization problems by exploiting the social behavior and individual characteristics of gray geese. GGO is developed based on the concept of gray geese flying in a V-shape, reducing air resistance, and covering longer distances than they would fly individually. This characteristic helps the proposed algorithm strike a balance between its exploration and exploitation stages. In optimal circumstances, there is paradigm-shifting in performance with repeated explorer geese-style systematic powerful random leaps within an area, seeking more efficient areas. The best solutions discovered through exploration are then utilized.

During hunting, roles are reversed, and every leader performs the required functions that characterize the manner in which geese become part of the flight to save energy. Role changes evade the risk of premature convergence while moving from one problem to another. Stressing social solidarity among geese, GGO also uses its communication to reach a solution. The interactive process between candidate solutions mimics the geese protecting and caring for each other to survive. The technique of the geese is to implement an effective search in high-dimensional space and utilize turning points that provide an optimal solution. Such characteristics make the technique a general-purpose one [45].

In solving the OPF problem using the GGO, each 'goose' in the flock represents a candidate operating point of the power system. This is seen as a solution vector that includes the key control variables: active levels of power generation, generator voltage magnitudes, transformer tap ratios, and shunt reactive power values. Every goose's 'fitness' is determined by the total cost of fuel, calculated from the objective function presented in Equation (2.4). The search done by the algorithm is constrained by the power system's operating constraints. This is achieved by utilizing a static penalty method, wherein an extensive penalty cost is added to the objective function of any goose whose corresponding solution vector violates the power flow equations or exceeds the specified limits on voltages, power output, or other variables. Utilizing this approach, the exploration and exploitation phases of GGO are focused within the feasible solution space, hence producing a valid and minimum-cost solution.

4. Results and Discussion

This section includes tables of results obtained in the course of the study, operating parameters, and information on working conditions. All experiments were performed under identical experimental conditions. For the 6-bus and 57-bus systems, population size was set as 30, iteration number as 100, and number of runs for each algorithm as 10. For the 30-bus system, population size was set as 40, iteration number as 100, and number of runs for each algorithm as 10. Average, standard deviation, and best fuel cost were determined by averaging the minimum fuel costs from 10 independent runs of the algorithms. The values obtained for the OPF problem constraints, i.e., P, V, Q, T, and QC values, were recorded and presented in table form. The values described in the tables are the constraint values obtained while finding the optimum convergence value in 10 individual runs. The work was performed on MATLAB R2021a using a computer system featuring Windows 10 Home Version 22H2 and an Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz.

Table 2. Parameters of the Used Metaheuristics Algorithm

	PS	G	DO	NRB	GG
	O	A	A	O	O
Exploration/Exploitation Phase Separation	-	-	%90 %10	-	-
Number of Groups	-	-	5	-	-
Avoidance Factor	-	-	-	0.6	-
Cognitive Coefficient	2	-	-	-	-
Social Coefficient	2	-	-	-	-
Inertia Coefficient	1	-	-	-	-

Table 2 displays the parameters and their values used for the techniques. For DOA, NRBO, and GGO, the parameter settings were taken from their original publications because no specific tuning was done.

Table 3. 6-bus Fixed Constraint Limits

	Lower bound	Upper bound	Unit
P ₂	30	100	MW
P ₃	20	60	MW
V ₂	0.90	1.10	p.u.
V ₃	0.90	1.10	p.u.
Q ₂	-50	50	MVAR
Q ₃	-40	40	MVAR
QC ₂	-0.4	0.4	p.u.
QC ₄	-0.3	0.3	p.u.
T	0.90	1.10	p.u.

Fixed constraint limits arrived at for the 6-bus system are presented in Table 3. Table 4 presents the results derived from the runs for the constraints arrived at for the 6-bus system.

Table 4. 6-bus Obtained Constraint Values

	PSO	GA	DOA	NRBO	GGO
P ₂	100.29	98.20	100.66	100.58	100.05
P ₃	52.9577	54.6281	52.7115	52.5842	54.2764
V ₂	1.05	1.05	1.05	1.05	1.05
V ₃	1.07	1.07	1.07	1.07	1.07
Q ₂	47.5892	44.0538	48.8069	47.1122	48.4995
Q ₃	85.2061	85.7320	86.0174	84.9184	85.6962
QC ₂	0.3988	0.3403	0.3999	0.4	0.0205
QC ₄	0.3	0.2991	0.2999	0.3	0.0961
T	0.9605	0.9545	0.9676	0.9581	0.9667

Table 5 presents the optimum value, average, and standard deviation of fuel costs arrived at from solving the 6-bus system.

Table 5. 6-bus Fuel Cost Values

	PSO	GA	DOA	NRBO	GGO
Best	450.46	450.78	450.46	450.46	451.00
Mean	450.53	451.11	450.59	450.48	451.59
Std	0.0472	0.2671	0.1954	0.0677	0.4103

According to the results, although the NRBO method had the optimal results for the 6-bus system, the PSO method also had an effective result based on having the lowest standard deviation value, along with no significant difference between the best-obtained values.

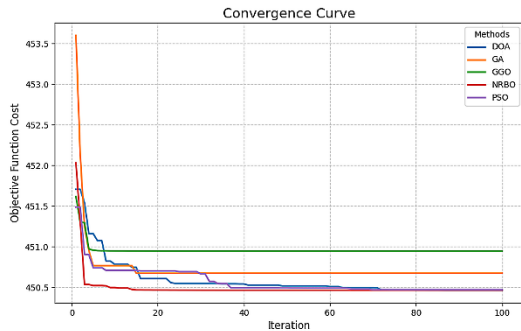


Figure 4. Convergence Curve for 6-bus System

Figure 4 illustrates the convergence behavior of algorithms. It is evident that NRBO converges rapidly to a high-quality solution within the initial iterations, whereas PSO exhibits a more gradual but stable convergence.

Table 6. Wilcoxon rank-sum results for 6-bus system

	p-value	h-value	Is significant
NRBO vs PSO	0,00228203501965665	1	Yes
NRBO vs GA	0,0001797009950484	1	Yes
NRBO vs DOA	0,00134916601663586	1	Yes
NRBO vs GGO	0,000131729603062133	1	Yes

To statistically validate these observations, a Wilcoxon rank-sum test was performed. The results, summarized in Table 6, indicate that NRBO's best cost was optimal, there was statistically significant difference between the performance of NRBO and other algorithms.

The fixed constraint values that are obtained for the 30-bus system are provided in Table 7.

Table 7. 30-bus Fixed Constraint Values

	Lower bound	Upper bound	Unit
P ₁	50	200	MW
P ₂	20	80	MW
P ₅	15	50	MW
P ₈	10	35	MW
P ₁₁	10	30	MW
P ₁₃	12	40	MW

V ₁	0.95	1.05	p.u.
V ₂	0.95	1.10	p.u.
V ₅	0.95	1.10	p.u.
V ₈	0.95	1.10	p.u.
V ₁₁	0.95	1.10	p.u.
V ₁₃	0.95	1.10	p.u.
T ₁₁	0.90	1.10	p.u.
T ₁₂	0.90	1.10	p.u.
T ₁₅	0.90	1.10	p.u.
T ₃₆	0.90	1.10	p.u.

The values of the constraints found by solving the 30-bus system are provided in Table 8.

Table 8. 30-bus Obtained Constraint Values

	PSO	GA	DOA	NRBO	GGO
P ₁	174.54	174.58	169.25	170.47	171.09
P ₂	49.92	54.23	47.30	47.87	46.51
P ₅	21.32	21.24	20.78	23.02	23.97
P ₈	18.30	17.29	18.79	22.32	18.60
P ₁₁	16.34	12.15	13.39	16.21	16.97
P ₁₃	12	13.46	22.04	12	15.15
V ₁	1.0809	1.0683	1.0999	1.0997	1.0723
V ₂	1.0651	1.0451	1.0872	1.0766	1.0481
V ₅	1.0534	0.9963	1.0602	1.0402	1.0116
V ₈	1.0602	1.0192	1.0701	1.0662	1.0264
V ₁₁	1.0640	1.0867	1.0999	1.0997	1.0466
V ₁₃	1.0866	1.0068	1.0995	1.0494	1.0517
T ₁₁	0.9220	1.0252	1.0235	1.0168	1.0553
T ₁₂	1.1	1.0582	1.0001	0.9532	0.9712
T ₁₅	1.1	1.0293	1.0119	0.9972	0.9674
T ₃₆	0.9704	0.9786	0.9887	0.9232	0.9741

Table 9 provides the statistical analysis of the fuel cost values found by solving the 30-bus system.

Table 9. 30-bus Fuel Cost Values

	PSO	GA	DOA	NRBO	GGO
Best	801.66	803.10	802.68	801.49	803.81
Mean	820.97	807.21	808.90	804.71	809.13
Std	17.88	4.20	4.50	3.13	7.12

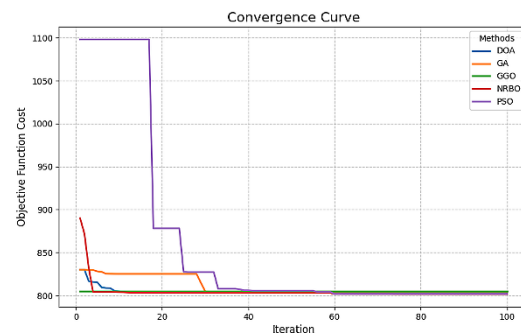


Figure 5. Convergence Curve for 30-bus System



For the 30-bus system, the superiority of NRBO is clearly demonstrated in its convergence curve (Figure 5), which shows both faster and deeper convergence compared to all other methods.

The statistical analysis presented in Table 10 confirms this visual observation. The performance of NRBO was found to be statistically superior to all other algorithms except GA.

Upon investigating the outcome derived in Table 9, it is seen that the NRBO method had the highest performance in terms of best value, average best value, and standard deviation value. Based on the results derived, the NRBO method is the most effective among the methods investigated to solve the 30-bus system.

Table 10. Wilcoxon rank-sum results for 30-bus system

	p-value	h-value	Is significant
NRBO vs PSO	0,01401927711396	1	Yes
NRBO vs GA	0,104109889660227	0	No
NRBO vs DOA	0,01401927711396	1	Yes
NRBO vs GGO	0,01401927711396	1	Yes

According to the calculated results, the PSO algorithm achieved the best value and average value score, whereas the NRBO algorithm achieved the best standard deviation score.

Table 11. 57-bus Fixed Constraint Values

	Lower Bound	Upper Bound	Unit
P ₁	0	400	MW
P ₂	0	100	MW
P ₃	0	140	MW
P ₆	0	100	MW
P ₈	0	550	MW
P ₉	0	100	MW
P ₁₂	0	400	MW
V ₁	0.94	1.06	p.u.
V ₂	0.94	1.06	p.u.
V ₃	0.94	1.06	p.u.
V ₆	0.94	1.06	p.u.
V ₈	0.94	1.06	p.u.
V ₉	0.94	1.06	p.u.
V ₁₂	0.94	1.06	p.u.
T ₄₋₁₈	0.90	1.10	p.u.
T ₂₁₋₂₀	0.90	1.10	p.u.
T ₂₄₋₂₆	0.90	1.10	p.u.

T ₇₋₂₉	0.90	1.10	p.u.
T ₃₄₋₃₂	0.90	1.10	p.u.
T ₁₁₋₄₁	0.90	1.10	p.u.
T ₁₅₋₄₅	0.90	1.10	p.u.
T ₁₄₋₄₆	0.90	1.10	p.u.
T ₁₀₋₅₁	0.90	1.10	p.u.
T ₁₃₋₄₉	0.90	1.10	p.u.
T ₁₁₋₄₃	0.90	1.10	p.u.
T ₄₀₋₅₆	0.90	1.10	p.u.
T ₃₉₋₅₇	0.90	1.10	p.u.
T ₉₋₅₅	0.90	1.10	p.u.
QC ₁₈	0	20	MVAR
QC ₂₅	0	20	MVAR
QC ₅₃	0	20	MVAR

The statistical outcome of the fuel expenses calculated based on the execution of the 57-bus system is demonstrated in Table 13.

Table 12. 57-bus Obtained Constraint Values

	PSO	GA	DOA	NRBO	GGO
P ₁	144.59	161.98	142.48	148.91	148.51
P ₂	94.26	82.16	98.07	65.58	70.26
P ₃	45.23	43.90	45.86	47.18	53.20
P ₆	67.72	80.51	57.19	90.62	62.42
P ₈	456.41	472.93	461.43	455.95	484.82
P ₉	95.67	77.98	90.57	95.39	88.76
P ₁₂	363.37	351.56	374.27	366.74	364.37
V ₁	1.04	1.04	1.04	1.04	1.04
V ₂	1.01	1.01	1.01	1.01	1.01
V ₃	0.985	0.985	0.985	0.985	0.985
V ₆	0.98	0.98	0.98	0.98	0.98
V ₈	1.005	1.005	1.005	1.005	1.005
V ₉	0.98	0.98	0.98	0.98	0.98
V ₁₂	1.015	1.015	1.015	1.015	1.015
T ₄₋₁₈	0.9057	0.9452	0.9286	1.0240	0.9394
T ₄₋₁₈	0.9021	1.0447	0.9790	0.9590	1.0182
T ₂₁₋₂₀	1.0118	1.0960	0.9839	0.9809	1.0092
T ₂₄₋₂₆	1.0189	1.0403	0.9451	0.9901	1.0661
T ₇₋₂₉	0.9	0.9307	0.9080	0.9307	1.0463
T ₃₄₋₃₂	0.9687	1.0204	1.0078	0.9581	0.9405
T ₁₁₋₄₁	0.9002	0.9005	0.9484	0.9332	1.0014
T ₁₅₋₄₅	0.9022	0.9042	1.0015	0.9318	0.9961
T ₁₄₋₄₆	0.9	0.9247	0.9978	0.9289	1.0307
T ₁₀₋₅₁	0.9072	0.9559	1.0049	0.9497	0.9795
T ₁₃₋₄₉	0.9000	0.9105	0.9438	0.9298	1.0118
T ₁₁₋₄₃	0.9000	0.9207	0.9348	1.0286	0.9941
T ₄₀₋₅₆	1.0353	1.0601	0.9848	1.0586	1.0399
T ₃₉₋₅₇	0.9998	1.0909	1.0289	1.0498	1.0201
T ₉₋₅₅	0.9000	0.9487	0.9299	0.9684	1.0189
QC ₁₈	0.526	9.110	19.814	12.366	9.177
QC ₂₅	19.729	19.664	19.373	14.349	7.839
QC ₅₃	18.156	9.297	19.968	13.250	15.957

Of the tested methods, although PSO showed good performance in solving the 57-bus system, the NRBO method must also be taken into account with respect to the difference in standard deviation.

Table 13. 57-bus Fuel Cost Values

	PSO	GA	DOA	NRBO	GGO
Best	41833.84	41902.73	41877.51	41891.52	41968.58
Mean	41864.32	42017.78	42047.54	41951.18	42180.22
Std	75.44	89.57	307.69	48.58	292.62

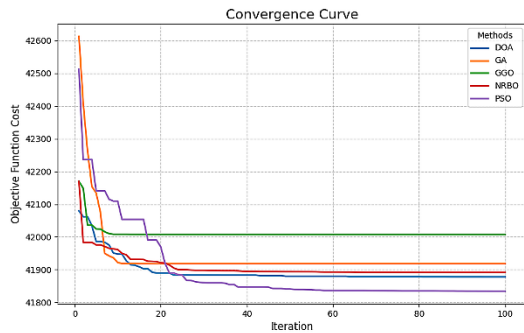


Figure 6. Convergence Curve for 57-bus System

On the large-scale 57-bus system, a trade-off between solution quality and stability becomes apparent (Figure 6). While PSO's convergence curve reaches a slightly lower final value on average, NRBO's curve shows less variability between runs.

Table 14. Wilcoxon rank-sum results for 57-bus system

	p-value	h-value	Is significant
PSO vs NRBO	0.0028273	1	Yes
PSO vs GA	0.0028273	1	Yes
PSO vs DOA	0.0017062	1	Yes
PSO vs GGO	0.00032984	1	Yes

To statistically validate these observations, a Wilcoxon rank-sum test was performed. The results, summarized in Table 14, indicate that PSO's best cost was solid.

It was verified whether the P, V, Q, T, and QC constraint values obtained from each run were within the IEEE bounds. All the methods remained within the constraints and produced results without any constraint violations during all runs. This is a demonstration of the stability of the chosen metaheuristic algorithms and constraint control systems. The lack of constraint violations indicates that the fuel costs are realistic and that the systems can be used under operating conditions.

5. Conclusion

The study illustrated a rigorous and extensive comparative analysis of five metaheuristic algorithms, including PSO, GA, DOA, NRBO, and GGO, for the optimal power flow problem of fuel cost minimization. The algorithms were compared under the same conditions on standard IEEE 6-bus, 30-bus, and 57-bus test systems to ensure unbiased and fair comparisons. Its performance was not only measured in terms of statistical values like best, mean, and standard deviation over 10 independent experiments but also through a qualitative analysis of their convergence behavior and statistical significance through the Wilcoxon rank-sum test.

The main findings of this research are highly sensitive to the size of the power system, experimentally confirming the "no-free lunch" theorem for this application problem. The major conclusions can hence be summarized as follows: Competitive performance of PSO and NRBO was observed in the small-size (6-bus) system. Even though NRBO selected the lowest absolute fuel cost, better stability and reliability were exhibited by PSO, even though a statistically significant difference was observed between their results. This means that for low-level systems, established techniques like PSO are still highly effective.

For the medium-size (30-bus) system, the Newton-Raphson-Based Optimizer (NRBO) was by far the best-performing algorithm. It outperformed all the others on best cost, mean cost, and standard deviation. Its quick and deep convergence, confirmed to be statistically significant, makes it an optimal choice for medium-complexity OPF problems.

For the large (57-bus) system, there was an obvious trade-off between solution quality and robustness. PSO produced the best mean fuel cost, showing its strong global search capability. NRBO, however, produced the most predictable and consistent results, as shown by its significantly lower standard deviation. This observation highlights that for large, complex systems, the algorithm selection may depend on operation priority: the minimum absolute cost versus good, consistent performance.

This work provides a helpful and up-to-date benchmark to the OPF literature, with relative strengths and weaknesses of the conventional as well as contemporary metaheuristics made apparent. Some possible avenues for future research are as follows. Firstly, the development of hybrid algorithms combining PSO's resilient exploration with NRBO's fast exploitation can produce better solutions for large systems. Second, the efficiency of these algorithms should be analyzed for multi-objective OPF problems with goals such as emission minimization and voltage stability. Finally, the

use of automated parameter tuning techniques could potentially enhance the performance and resilience of the evaluated algorithms.

Author's Contributions

Alper Buğra Polat: Drafted and wrote the manuscript, performed the experiment and result analysis.

Osman Altay: Assisted in analytical analysis on the structure, supervised the experiment's progress, result interpretation and helped in manuscript preparation.

Ethics

There are no ethical issues after the publication of this manuscript.

References

- [1] Tang, Y., Dvijotham, K., & Low, S. (2017). Real-time optimal power flow. *IEEE Transactions on Smart Grid*, 8(6), 2963-2973.
- [2] Risi, B. G., Riganti-Fulginei, F., & Laudani, A. (2022). Modern techniques for the optimal power flow problem: State of the art. *Energies*, 15(17), 6387.
- [3] Frank, S., & Rebennack, S. (2016). An introduction to optimal power flow: Theory, formulation, and examples. *IEE transactions*, 48(12), 1172-1197.
- [4] Cain, M. B., O'neill, R. P., & Castillo, A. (2012). History of optimal power flow and formulations. *Federal Energy Regulatory Commission*, 1, 1-36.
- [5] Cabadağ, R. I., Türkay, B. E., & Tunç, A. (2011). Optimal Güç Akışı Çözümlerinde Lineer Programlama ve İç nokta Algoritması Yöntemlerinin Karşılaştırmalı Analizi, II. Elektrik Tesisat Ulusal Kongresi, 24-27 Kasım 2011, İzmir.
- [6] Ebeed, M., Kamel, S., & Jurado, F. (2018). Optimal power flow using recent optimization techniques. In *Classical and recent aspects of power system optimization* (pp. 157-183). Academic Press.
- [7] Altay, E. V., & Altay, O. (2021). Güncel metasezgisel optimizasyon algoritmalarının CEC2020 test fonksiyonları ile karşılaştırılması. *Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi*, 12(5), 729-741.
- [8] Abdel-Basset, M., Abdel-Fatah, L., & Sangaiyah, A. K. (2018). Metaheuristic algorithms: A comprehensive review. *Computational intelligence for multimedia big data on the cloud with engineering applications*, 185-231.
- [9] Halim, A. H., Ismail, I., & Das, S. (2021). Performance assessment of the metaheuristic optimization algorithms: an exhaustive review. *Artificial Intelligence Review*, 54(3), 2323-2409.
- [10] Nagarajan, K., Rajagopalan, A., Bajaj, M., Raju, V., & Blazek, V. (2025). Enhanced wombat optimization algorithm for multi-objective optimal power flow in renewable energy and electric vehicle integrated systems. *Results in Engineering*, 25, 103671.
- [11] Shu, H., Zhao, H., & Liao, M. (2025). Optimal power flow in hybrid AC-DC systems considering Nk security constraints in the preventive-corrective control stage. *Electric Power Systems Research*, 238, 111052.
- [12] Mahela, O. P., & Ola, S. R. (2013). Optimal capacitor placement for loss reduction in electric transmission system using genetic algorithm. *TJPRC-International Journal of Electrical and Electronics Engineering Research*, 3(2), 59-68.
- [13] Mohamed, S. A., Anwer, N., & Mahmoud, M. M. (2025). Solving optimal power flow problem for IEEE-30 bus system using a developed particle swarm optimization method: towards fuel cost minimization. *International Journal of Modelling and Simulation*, 45(1), 307-320.
- [14] Zhai, C., Zhang, H., Xiao, G., & Pan, T. C. (2019). A model predictive approach to protect power systems against cascading blackouts. *International Journal of Electrical Power & Energy Systems*, 113, 310-321.
- [15] Hamadneh, T., Batiha, B., Gharib, G. M., Montazeri, Z., Dehghani, M., Aribowo, W., ... & Eguchi, K. (2025). Builder optimization algorithm: an effective human-inspired metaheuristic approach for solving optimization problems. *International Journal of Intelligent Engineering and Systems*, 18(3), 928-937.
- [16] Dehghani, M., Hubálovský, Š., & Trojovský, P. (2021). Northern goshawk optimization: a new swarm-based algorithm for solving optimization problems. *Ieee Access*, 9, 162059-162080.
- [17] Xie, L., Han, T., Zhou, H., Zhang, Z. R., Han, B., & Tang, A. (2021). Tuna swarm optimization: a novel swarm-based metaheuristic algorithm for global optimization. *Computational intelligence and Neuroscience*, 2021(1), 9210050.
- [18] Dehghani, M., Hubálovský, Š., & Trojovský, P. (2021). Cat and mouse based optimizer: a new nature-inspired optimization algorithm. *Sensors*, 21(15), 5214.
- [19] Neshat, M., Sepidnam, G., & Sargolzaei, M. (2013). Swallow swarm optimization algorithm: a new method to optimization. *Neural Computing and Applications*, 23(2), 429-454.
- [20] Taheri, A., RahimiZadeh, K., Beheshti, A., Baumbach, J., Rao, R. V., Mirjalili, S., & Gandomi, A. H. (2024). Partial reinforcement optimizer: An evolutionary optimization algorithm. *Expert Systems with Applications*, 238, 122070.
- [21] Cheraghalipour, A., Hajiaghahi-Keshteli, M., & Paydar, M. M. (2018). Tree Growth Algorithm (TGA): A novel approach for solving optimization problems. *Engineering Applications of Artificial Intelligence*, 72, 393-414.
- [22] Price, K. V., Storn, R. M., & Lampinen, J. A. (2005). The differential evolution algorithm. *Differential evolution: a practical approach to global optimization*, 37-134.
- [23] Erol, O. K., & Eksin, I. (2006). A new optimization method: big bang-big crunch. *Advances in engineering software*, 37(2), 106-111.
- [24] Hashim, F. A., Hussain, K., Houssein, E. H., Mabrouk, M. S., & Al-Atabany, W. (2021). Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems. *Applied intelligence*, 51, 1531-1551.
- [25] Ghannadi, P., & Kourehli, S. S. (2020). Multiverse optimizer for structural damage detection: Numerical study and experimental validation. *The Structural Design of Tall and Special Buildings*, 29(13), e1777.
- [26] Kaveh, A., & Dadras, A. (2017). A novel meta-heuristic optimization algorithm: thermal exchange optimization. *Advances in engineering software*, 110, 69-84.
- [27] Rao, R. V., Savsani, V. J., & Vakharia, D. P. (2011). Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems. *Computer-aided design*, 43(3), 303-315.

- [28] Mousavirad, S. J., & Ebrahimpour-Komleh, H. (2017). Human mental search: a new population-based metaheuristic optimization algorithm. *Applied Intelligence*, 47, 850-887.
- [29] Shi, Y. (2015). An optimization algorithm based on brainstorming process. In *Emerging Research on Swarm Intelligence and Algorithm Optimization* (pp. 1-35). IGI Global.
- [30] Purnomo, H. D., & Wee, H. M. (2013). Soccer game optimization: an innovative integration of evolutionary algorithm and swarm intelligence algorithm. In *Meta-Heuristics optimization algorithms in engineering, business, economics, and finance* (pp. 386-420). Igi Global.
- [31] Dehghani, M., & Trojovský, P. (2021). Teamwork optimization algorithm: A new optimization approach for function minimization/maximization. *Sensors*, 21(13), 4567.
- [32] Dehghani, M., Montazeri, Z., Givi, H., Guerrero, J. M., & Dhiman, G. (2020). Darts game optimizer: A new optimization technique based on darts game. *International Journal of Intelligent Engineering and Systems*, 13(5), 286-294.
- [33] Bakır, H. (2024). Optimal power flow analysis with circulatory system-based optimization algorithm. *Turkish Journal of Engineering*, 8(1), 92-106. <https://doi.org/10.31127/tuje.1282429>
- [34] Guvenc, U., Bakir, H., Duman, S., Ozkaya, B. (2021). Optimal Power Flow Using Manta Ray Foraging Optimization. In: Hemanth, J., Yigit, T., Patrut, B., Angelopoulou, A. (eds) *Trends in Data Engineering Methods for Intelligent Systems. ICAIAME 2020. Lecture Notes on Data Engineering and Communications Technologies*, vol 76. Springer, Cham. https://doi.org/10.1007/978-3-030-79357-9_14
- [35] Duman, S., Kahraman, H.T., Korkmaz, B., Bakir, H., Guvenc, U., Yilmaz, C. (2023). Improved Phasor Particle Swarm Optimization with Fitness Distance Balance for Optimal Power Flow Problem of Hybrid AC/DC Power Grids. In: *Smart Applications with Advanced Machine Learning and Human-Centred Problem Design. ICAIAME 2021. Engineering Cyber-Physical Systems and Critical Infrastructures*, vol 1. Springer, Cham. https://doi.org/10.1007/978-3-031-09753-9_24
- [36] Bakir, H., Guvenc, U. & Kahraman, H.T. Optimal operation and planning of hybrid AC/DC power systems using multi-objective grasshopper optimization algorithm. *Neural Comput & Applic* 34, 22531–22563 (2022). <https://doi.org/10.1007/s00521-022-07670-y>
- [37] Bakır, H., Kahraman, H. T., Yılmaz, S., Duman, S., & Guvenc, U. (2024). Dynamic switched crowding-based multi-objective particle swarm optimization algorithm for solving multi-objective AC-DC optimal power flow problem. *Applied Soft Computing*, 166, 112155. <https://doi.org/10.1016/J.ASOC.2024.112155>
- [38] Bakır, H., Duman, S., Guvenc, U., & Kahraman, H. T. (2023). A novel optimal power flow model for efficient operation of hybrid power networks. *Computers and Electrical Engineering*, 110, 108885. <https://doi.org/10.1016/J.COMPELECENG.2023.108885>
- [39] Bakir, H., Guvenc, U., Duman, S., & Kahraman, H. T. (2023). Optimal Power Flow for Hybrid AC/DC Electrical Networks Configured With VSC-MTDC Transmission Lines and Renewable Energy Sources. *IEEE Systems Journal*, 17(3), 3938–3949. <https://doi.org/10.1109/JSYST.2023.3248658>
- [40] Bakır, H. (2024). Dynamic fitness-distance balance-based artificial rabbits optimization algorithm to solve optimal power flow problem. *Expert Systems with Applications*, 240, 122460. <https://doi.org/10.1016/J.ESWA.2023.122460>
- [41] Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks* (Vol. 4, pp. 1942-1948). ieee.
- [42] Kramer, O., & Kramer, O. (2017). *Genetic algorithms* (pp. 11-19). Springer International Publishing.
- [43] Lang, Y., & Gao, Y. (2025). Dream Optimization Algorithm (DOA): A novel metaheuristic optimization algorithm inspired by human dreams and its applications to real-world engineering problems. *Computer Methods in Applied Mechanics and Engineering*, 436, 117718.
- [44] Sowmya, R., Premkumar, M., & Jangir, P. (2024). Newton-Raphson-based optimizer: A new population-based metaheuristic algorithm for continuous optimization problems. *Engineering Applications of Artificial Intelligence*, 128, 107532.
- [45] El-Kenawy, E. S. M., Khodadadi, N., Mirjalili, S., Abdelhamid, A. A., Eid, M. M., & Ibrahim, A. (2024). Greylag goose optimization: nature-inspired optimization algorithm. *Expert Systems with Applications*, 238, 122147.