ISSN: 2583-9292 (ONLINE)
DOI: 10.xx/ijdsml.2025.xx

ADVANCED MULTI-CRITERIA OPTIMIZATION STRATEGY FOR TACKLING COMPLEX MANY-OBJECTIVE OPTIMAL POWER FLOW CHALLENGES

Abhishek Bajirao Katkar[1] and Himmat Tukaram Jadhav[2]
[1]Department of Electrical Engineering, Government Polytechnic, Kolhapur, India
[2]Faculty of Science and Technology, SNDT Women's University, India

Abstract

This research presents an advanced multi-criteria optimisation strategy to address the complex challenges associated with many-objective optimal power flow (MOOPF). This study presents a hybrid algorithm that combines the Multiobjective Artificial Bee Colony (MOABC) algorithm with the Non-dominated Sorting Genetic Algorithm II (NSGA-II), optimising the balance between exploration and exploitation in the search space. The hybrid MOABC-NSGAII algorithm is rigorously evaluated using the IEEE CEC 2023 benchmark test instances, showcasing its robustness, efficiency, and ability to address complex optimisation challenges. Subsequent to the comprehensive benchmarking, the algorithm is implemented on the IEEE 118 bus system, to address complex real-time optimisation scenarios. This study aims to concurrently minimise the fuel costs of thermal generators, active power losses, and deviations in voltage magnitude. The research seeks to improve the economic efficiency, reliability, and environmental sustainability of the power system through the optimisation of three critical parameters. The findings from IEEE CEC benchmark test and MOOPF IEEE 118 bus system case study analysis confirm the effectiveness of the proposed hybrid algorithm, demonstrating notable enhancements in attaining a balanced and optimised power system operation. This investigation highlights the effectiveness of hybrid MOABC-NSGAII in addressing many-objective tasks with statistical validation of performance metrics proves its applications in large-scale power system management.

Keywords:

Multi-Objective Optimization, Optimal Power Flow, Hybrid ABC-NSGAII, CEC Benchmark Functions

1. INTRODUCTION

Recently, the operation, control, and management of power systems have become more complicated and difficult. The system severity value should be minimized to improve power system security and to avoid line overloading, bus voltage limit violations, and finally, line outage conditions. The transmission of bulk power and the difference in the loading pattern from the originally planned pattern affect the complexity of the power monitoring system. Hence, to secure and stabilize the operation of a power system, optimal power flow (OPF) performs a crucial role. Optimization of the considered objective functions, such as generation cost, transmission loss, and severity value minimization, is the first target of the OPF problem. Recently, many heuristic optimization techniques have been proposed to solve the problems in power systems, such as the cost of power generation, transmission power loss, and severity value minimization. The operation, control, and management of power systems have recently grown more complex and challenging.

Traditional distribution grids, which are designed for passive operation characterised by a radial topology and unidirectional power flows towards the transformer, lack the capacity to accommodate substantial levels of distributed generation (DG). To address the anticipated increase in demand, it is crucial to implement infrastructure upgrades and adopt new technologies for monitoring and regulation. Enhancing investments in existing grid infrastructure is essential for transitioning to future grid models capable of integrating new renewable energy sources (RES) and increased loads. The optimal power flow (OPF) problem is essential for informing energy distribution companies regarding optimal investment strategies in this challenging context. Real-time energy market regulation necessitates constraints that impact the attainment of optimal load flow results. The primary objective of the OPF problem is the optimisation of objective functions, including generation cost, gearbox loss, and voltage profile enhancement. Heuristic optimisation techniques have been extensively proposed to tackle challenges associated with power generation costs, transmission losses, and the minimisation of voltage deviation.

This research presents an advanced multi-criteria optimisation strategy aimed at addressing the complexities associated with many-objective optimal power flow (MOOPF). A hybrid algorithm is developed that integrates the strengths of the Multiobjective Artificial Bee Colony (MOABC) algorithm with the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The hybrid MOABC-NSGAII algorithm achieves an effective balance between exploration and exploitation in the search space. The method undergoes thorough evaluation using the IEEE CEC 2023 benchmark test instances, showcasing its robustness, efficiency, and ability to address complex optimisation challenges. The algorithm is applied to the IEEE 118 bus system, a large-scale power system, to optimise and minimise three key objectives: fuel cost of thermal generators, active power loss, and voltage magnitude deviation. The findings demonstrate notable enhancements in power system operation, confirming the efficacy of the proposed method for addressing complex, multi-objective optimisation challenges in power systems.

This paper examines classical and contemporary methods, including probabilistic and metaheuristic approaches, with a focused analysis on applications related to grid topology. The non-dominated sorting hybrid multi-objective artificial bee colony (NSHMABC) algorithm, which integrates NSGA-II and ABC algorithms, is utilised for addressing single and multi-objective optimisation problems, improving voltage profiles through the assessment of voltage deviation. Solutions from the Pareto set are chosen based on user preferences through a fuzzy decision-making mechanism. The proposed method was evaluated using the three-objective IEEE 118 bus standard test system. The results obtained were compared with those in existing literature, highlighting the superiority and practical applicability of the proposed approach.

2. LITERATURE REVIEW AND RESEARCH GAP

Several metaheuristic algorithms, including the hybrid cuckoo search algorithm, have been studied to address convergence [2]. The firefly algorithm was used to analyse the OPF solution's unoptimised cost, loss, and emission objective functions [3]. Power system security was improved with a multi-objective multi-population ant colony algorithm [4]. The OPF problem was solved with a dynamic population-based ABC algorithm. The results were compared to NSGA-II and multi-objective ABC [5]. The linear OPF method optimised generator dispatch by linearising AC load flow equations. The LOPF method is seven times faster than existing methods [6]. TLBO is used to solve multi-objective OPF problems in this article. The proposed method was tested with 9- and 26-bus systems. To optimise power system issues, cost, power loss, and voltage deviation were minimised. The results were compared to a mixed-integer PSO algorithm [7]. The fruit fly algorithm's convergence for engineering optimisation problems is lower than the ABC algorithm [8]. Using knowledge, a MOFOA could reduce cost and make span. The non-dominated sorting method optimises multi-objective problems [9]. The enhanced fruit fly method for engineering design problems was compared to GA, PSO, and DSLC-FOA [10]. A reproduction operator and two-archive concept improved the basic MGWO. This approach was used to solve the multi-objective reactive power dispatch problem [11]. This hybrid multi-objective genetic algorithm reduced optimal power flow calculation computational cost [12]. The optimal reactive dispatch problem was solved using the artificial bee colony with firefly (ABCFF) algorithm [13], and multi-objective optimal power flow (OPF) problems were solved using the novel quasi-oppositional modified Jaya (QOMJaya) algorithm [14]. Optimal power flow (OPF) problems are solved using the sine–cosine algorithm [15], while multi-objective optimisation problems are solved using the spotted hyena optimiser [16]. Firefly was introduced to solve optimisation problems [17]. The optimal power flow (OPF) problem was solved using moth swarm [18]. To minimise objective functions, convexified multi-objective models for optimal power flow were used [19]. Two test systems assessed the tree seed algorithm's OPF performance [20]. A heuristic Fuzzy Adaptive Heterogeneous Comprehensive-Learning Particle Swarm Optimisation algorithm was used to find optimal reactive power dispatch solutions [21], while Shuffled Frog Leaping was used to solve the OPF problem with FACTS controllers [22]. Authors have suggested PSO, ABC, and NSGA-II for multi-objective optimisation in various applications [23–28]. The single-objective optimisation problem was solved using social spider optimisation [29]. The PSO algorithm solved OPF problems with and without FACTS controllers [30]. In the current study, function severity under abnormal conditions, including line outages, was not considered. The proposed algorithm was improved by hybridising the selected algorithms. This paper introduces a hybrid NSGAII-based artificial bee colony (NSHMOABC) objective parameter optimisation algorithm. Historically, weighted sum and constraint methods solved multi-objective optimisation problems. This study proposes NSHMOABC, a non-dominated sorting hybrid fruit fly-based artificial bee colony algorithm. Standard test functions and the IEEE 118 bus system were tested with the proposed algorithm.

In this paper, section 4 describes the proposed Hybrid ABC-NSGA II algorithm, Section 4 IEEE CEC 2023 benchmark suite test function, section 5 describes the MOOPF 118 bus system case study, and section 6 presents results and analysis for proposed algorithm along statistical validation using performance metrics

3. NON-DOMINATED SORTING MULTI-OBJECTIVE ARTIFICIAL BEE COLONY ALGORITHM

3.1 MULTI-OBJECTIVE ARTIFICIAL BEE COLONY ALGORITHM:

The Multi-objective Artificial Bee Colony (MOABC) algorithm is derived from the foraging behaviour of honeybees. This approach effectively addresses complex problems characterised by multiple conflicting objectives, rendering it suitable for real-world applications that necessitate the balancing of criteria. This article outlines the MOABC algorithm, detailing its components and applications.:

- **Foraging Behavior:** Honeybees find food and tell other bees about it, which inspired the MOABC algorithm. This collective behaviour helps bees find the best food sources. This principle helps the algorithm exploit search space in optimisation problems.
- **Swarm Intelligence:** Decentralised, self-organised systems behave like swarm intelligence. All MOABC bees are potential optimisation solutions. The swarm shares information and adjusts positions based on individual and collective experiences to find the best solutions.

3.2 KEY COMPONENTS

1. **Initialization:** A bee population is randomly initialised to start the algorithm. Each bee represents an objective-valued candidate solution. This initial population is distributed across the search space to explore all possible solutions.
2. **Employed Bees Phase:** Each employed bee searches its neighbourhood for a better solution in this phase. This is like a bee looking for better food nearby. The bee moves to the new position if the new solution is better.
3. **Onlooker Bees Phase:** Onlooker bees use employed bees' information to find food. The selection is probabilistic, with better solutions having a better chance. This process mimics how natural bees choose the best food sources based on peer feedback.
4. **Scout Bees Phase:** Scout bees are employed bees that fail to find a better solution after a certain number of trials. Scout bees randomly search for new solutions. This phase keeps the algorithm out of local optima and ensures global search.
5. **Solution Update:** Employed, onlooker, and scout bees share and update their best solutions. We keep going until we reach a stopping point, like a maximum number of iterations or a good solution quality.

3.3 FEATURES OF THE MULTI-OBJECTIVE ARTIFICIAL BEE COLONY (MOABC) ALGORITHM

Swarm intelligence and honey bee optimisation are used by the Multi-objective Artificial Bee Colony (MOABC) algorithm to efficiently navigate the search space, balancing conflicting objectives and maintaining diversity through its phased approach. It adapts to different problem landscapes, ensuring robustness and flexibility across domains and fast convergence to optimal or near-optimal solutions. However, parameter sensitivity, scalability issues in large or high-dimensional search spaces, and diversity-related computational costs plague the MOABC algorithm. The quality of the initial population, complexity in balancing exploration and exploitation, and need for extensive customisation for specific applications also affect its performance. Despite these drawbacks, MOABC can be used for multi-objective optimisation with careful tuning and problem-specific adjustments.

3.4 NON-DOMINATED SORTING GENETIC ALGORITHM-II

Popular multi-objective optimisation algorithm NSGA-II solves problems with multiple conflicting objectives. Deb et al. proposed it in 2002 as an improvement over NSGA1.

3.4.1 Features:

- **Non-Dominated Sorting**: NSGA-II ranks solutions by dominance using non-dominated sorting. Non-dominated solutions (Pareto optimal solutions) are in the first front.
- **Crowding Distance**: NSGA-II calculates crowding distance for each solution to maintain population diversity. This metric measures the objective space density of solutions surrounding a solution to ensure even distribution.
- **Elitism**: Elite solutions are preserved from generation to generation by the algorithm, preventing their loss during evolution.
- **Binary Tournament Selection**: A binary tournament selects mating solutions based on rank and crowding distance in NSGA-II. The solution with lower rank and higher crowding distance wins.
- **Crossover and Mutation**: SBX and PM are used to generate new offspring solutions by the algorithm.
- **Diversity Preservation**: NSGA-II preserves population diversity by combining non-dominated sorting and crowding distance, preventing premature convergence to suboptimal solutions.

3.4.2 Stepwise Procedure of Working Procedure as follows:

- **Initialization**: The algorithm starts with a randomly generated initial population of solutions.
- **Evaluation**: Each solution in the population is evaluated based on the given objective functions.
- **Non-Dominated Sorting**: Solutions are sorted into different fronts based on their dominance relationships.
- **Selection**: A binary tournament selection process is used to select parent solutions for mating.
- **Crossover and Mutation**: Offspring solutions are generated using crossover and mutation operators.
- **Survival Selection**: The combined population of parents and offspring is sorted again, and the best solutions are selected to form the new population.
- **Termination**: The algorithm repeats the evaluation, selection, and survival steps until a stopping criterion till, such as a maximum number of generations or a solution quality.

3.5 NON-DOMINATED SORTING GENETIC ALGORITHM II

NSGA-II has several features that make it stand out compared to other multi-objective evolutionary algorithms (MOEAs). The NSGA-II algorithm efficiently solves large-scale optimisation problems by balancing exploration and exploitation to quickly converge to optimal or near-optimal solutions. Its versatility makes it suitable for multi-objective optimisation problems in engineering design and healthcare. The algorithm solves benchmark problems well and maintains solution diversity. Its simplicity has also made it popular in academic research and practice. However, NSGA-II has limitations. Population size and mutation rate affect its performance. Scalability issues may arise with large or high-dimensional problems, and implementation and tuning complexity must be considered. Its convergence speed depends on problem complexity and search space landscape, but it is generally efficient. A hybrid approach using NSGA-II and MOABC can overcome these limitations. Exploration, exploitation, and solution diversity are balanced in the hybrid model to improve performance in complex multi-objective optimisation problems.

3.6 OVERCOMING INDIVIDUAL LIMITATIONS

- **Enhanced Exploration and Exploitation**: MOABC's swarm intelligence-based exploration and NSGA-II's efficient exploitation through non-dominated sorting and elitism improve the hybrid algorithm's ability to search and exploit promising regions. This method improves diversity maintenance because MOABC scout bees prevent premature convergence and NSGA-II's crowding distance mechanism evenly distributes solutions across the Pareto front. The hybrid algorithm handles complex and dynamic multi-objective optimisation landscapes efficiently due to its robustness and flexibility. The hybrid approach accelerates convergence to high-quality solutions, balances exploration to avoid local optima, and efficiently refines solutions by integrating both algorithms. It also uses constraint handling mechanisms from both algorithms to optimise objectives and meet problem constraints for real-world applications. Exploration and exploitation are balanced to reduce computational costs and optimise the algorithm for large problems.

3.7 STEPWISE OPERATIONS OF HYBRID MOABC AND NSGA-II APPROACH

1) **Initialization**:
    a) **Step 1**: Initialize a population P with N random solutions.

b) **Step 2**: Evaluate the objective values of each solution in P.

c) **Step 3**: Perform non-dominated sorting on P to determine Pareto fronts.

d) **Step 4**: Calculate the crowding distance for each solution in P.

2) **Main Loop**: Repeat until a termination criterion (e.g., maximum number of iterations, convergence) is met.

a) **Employed Bee Phase (ABC)**:

i) **Step 5**: For each employed bee in P:

(1) Generate a new solution by modifying the current solution using neighborhood search.

(2) Evaluate the objective values of the new solution.

(3) If the new solution dominates the current solution, replace the current solution with the new solution.

b) **Onlooker Bee Phase (ABC)**:

i) **Step 6**: Select solutions based on their fitness (using Pareto front and crowding distance).

ii) **Step 7**: For each onlooker bee:

(1) Generate a new solution based on selected solutions.

(2) Evaluate the objective values of the new solution.

(3) If the new solution dominates the current solution, replace the current solution with the new solution.

c) **Scout Bee Phase (ABC)**:

i) **Step 8**: For each scout bee in P:

(1) If a solution has not improved for a certain number of iterations, replace the solution with a new random solution.

d) **Crossover and Mutation (NSGA-II)**:

i) **Step 9**: Combine the current population P and the newly generated offspring into a new population Q.

ii) **Step 10**: For each pair of parent solutions selected based on binary tournament selection from P:

(1) Perform crossover to generate offspring.

(2) Perform mutation on offspring.

iii) Add the offspring to Q.

e) **Evaluation**:

i) **Step 11**: Evaluate the objective values of each solution in Q.

f) **Non-Dominated Sorting and Crowding Distance Calculation (NSGA-II)**:

i) **Step 12**: Perform non-dominated sorting on Q to determine Pareto fronts.

ii) **Step 13**: Calculate the crowding distance for each solution in Q.

g) **Selection (NSGA-II)**:

i) **Step 14**: Select the N best solutions from Q based on their Pareto rank and crowding distance to form the new population P.

1. ***Termination***:

○ ***Step 15**: When the termination criteria are met, return the Pareto optimal solutions in P*

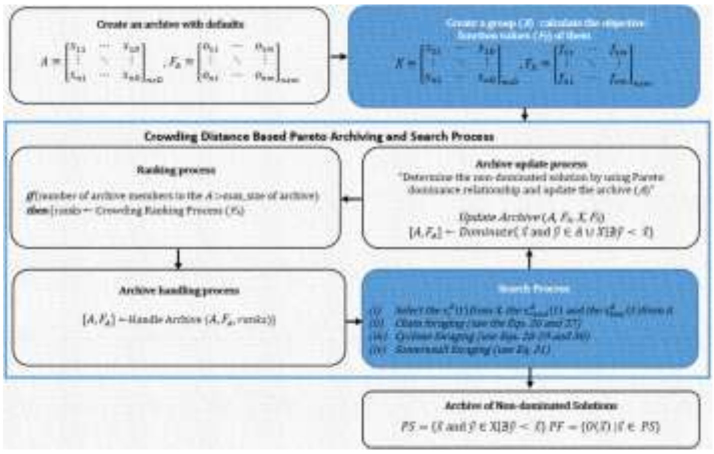

Fig.1. Flowchart and mathematical formulations of Hybrid ABC-NSGAII working Procedure

4. BENCHMARK TEST FUNCTIONS

Introducing a new benchmark problem allows algorithms to be evaluated in a real-world scenario, but this may not fully capture the algorithm's robustness. The CEC2023 test suite must include benchmark problems for a complete assessment. These benchmarks assess multi-objective optimisation algorithms' scalability, complexity, and constraint-handling. Constrained MOOPF problems are among evolutionary computation research's hardest. To solve, you must consider constraints and objective functions simultaneously. This led to many constraint-handling methods. Considering these two points, this paper begins by building IEEE CEC 2023 test instances with different properties. To apply MOOPF to performance differences under different conditions, we combine it with nondominated sorting genetic algorithm II.

Dynamic Constrained Multiobjective Optimization (DCMO)

Benchmark Function	Mathematical Formulation	Range/Constraints	Variables/Objective Functions
DCMO1	$f_1(x) = x_1$ $f_2(x) = 1 - \sqrt{x_1} + 2\sum_{i=2}^{n} x_i$	$0 \le x_i \le 1$	Variables: $x = (x_1, \ldots, x_n)$ Objectives: f_1, f_2
DCMO2	$f_1(x) = x_1$ $f_2(x) = 1 - \sqrt{x_1} + \sum_{i=2}^{n} (x_i^2 - \cos(2\pi x_i) + 1)$	$0 \le x_i \le 1$ $g(x) \le 0$	Variables: $x = (x_1, \ldots, x_n)$ Objectives: f_1, f_2

Evolutionary Multi-task Optimization (EMTO)

Benchmark Problem	Mathematical Formulation	Range/Constraints	Variables/Objective Functions
MTSOO1	$f(x) = \sum_{i=1}^{n} x_i^2$	$-100 \le x_i \le 100$	Variables: $x = (x_1, \ldots, x_n)$ Objective: f
MTSOO2	$f(x) = \sum_{i=1}^{n} (x_i - 1)^2$	$-100 \le x_i \le 100$	Variables: $x = (x_1, \ldots, x_n)$ Objective: f
MTMOO1	$f_1(x) = x_1$ $f_2(x) = 1 - x_1 + 2\sum_{i=2}^{n} x_i$	$0 \le x_i \le 1$	Variables: $x = (x_1, \ldots, x_n)$ Objectives: f_1, f_2

Large-scale Continuous Optimization for Non-contact Measurement

Benchmark Problem	Mathematical Formulation	Range/Constraints	Variables/Objective Functions
LSOP1	$f(x) = \sum_{i=1}^{n} (x_i - 2)^2$	$-100 \le x_i \le 100$	Variables: $x = (x_1, \ldots, x_n)$ Objective: f
LSOP2	$f(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10)$	$-100 \le x_i \le 100$	Variables: $x = (x_1, \ldots, x_n)$ Objective: f

Constrained Multimodal Multiobjective Optimization (CMMO)

Benchmark Problem	Mathematical Formulation	Range/Constraints	Variables/Objective Functions
CMMO1	$f_1(x) = x_1$ $f_2(x) = g(x)\left(1 - \sqrt{\frac{x_1}{g(x)}}\right)$ $g(x) = 1 + 9\sum_{i=2}^{n} x_i$	$0 \le x_i \le 1$	Variables: $x = (x_1, \ldots, x_n)$ Objectives: f_1, f_2
CMMO2	$f_1(x) = x_1$ $f_2(x) = g(x)\left(1 - \left(\frac{x_1}{g(x)}\right)^2\right)$ $g(x) = 1 + 10\sum_{i=2}^{n} x_i$	$0 \le x_i \le 1$	Variables: $x = (x_1, \ldots, x_n)$ Objectives: f_1, f_2

Fig.2. IEEE CEC 2023 Benchmark test instance suite

PlatEMO is an open-source MATLAB platform tailored for evolutionary multi-objective optimisation (EMO). It accommodates a diverse array of algorithms and problems, rendering it suitable for comparative reviews [70]. Utilising PlatEMO's experiment module allows for the efficient evaluation and comparison of various algorithms across different optimisation problems, the export of statistical results, and the exploration of new algorithmic possibilities, all within a user-friendly interface that supports research objectives.

4.1 PERFORMANCE METRICS

4.1.1 Hypervolume Indicator:

The Hypervolume Indicator serves as a performance metric for assessing the quality of solution sets in multi-objective optimisation. The measurement pertains to the volume, or area in two-dimensional cases, within the objective space that is encompassed by the solution set and constrained by a reference point. The reference point is typically selected to ensure that all solutions are superior to it. The hypervolume signifies convergence and diversity. A larger hypervolume signifies that the solutions are nearer to the optimal Pareto front. Diversity in solutions enhances coverage across a broader spectrum within the objective space.

To calculate the hypervolume, one must: Choose a reference point that is superior to all solutions. Partition the objective space into hyper-rectangles defined by the solutions and the reference point. A higher Hypervolume value indicates a better performance of the algorithm in terms of these two aspects. All simulations upto 30 runs with bold highlighted numbers as the best results.

Table.1. Mean hypervolume (HV)

Problems	SPEA-II	NSGA-I	MOEA/D	NSGA-II	NSGA-III	MOABC	ABC-NSGAII
DCMO1	4.92E-01	4.26E-01	6.17E-01	6.86E-01	1.26E-01	6.87E-01	**7.58E-01**
DCMO2	5.25E-01	5.56E-01	5.55E-01	5.55E-01	5.09E-01	5.59E-01	5.38E-01
MTSOO1	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	**1.04E-01**
MTSOO2	4.69E-01	**4.29E-01**	3.32E-01	4.57E-01	4.99E-01	3.65E-01	**5.43E-01**
MTMOO1	1.98E-01	1.94E-01	1.82E-01	**1.99E-01**	1.89E-01	**1.92E-01**	**1.99E-01**
LSOP1	1.94E-01	1.91E-01	1.55E-01	2.00E-01	2.00E-01	**1.91E-01**	**2.00E-01**
LSOP2	2.48E-01	2.46E-01	2.34E-01	2.71E-01	2.69E-01	2.62E-01	2.71E-01
CMMO1	**6.35E-01**	5.98E-01	0.00E+00	5.36E-01	0.00E+00	0.00E+00	6.46E-01
CMMO2	3.01E-01	2.79E-01	4.06E-03	2.66E-01	1.56E-01	1.63E-02	3.16E-01

4.1.2 Inverted Generational Distance (IGD):

The Inverted Generational Distance (IGD) serves as a metric for assessing the degree to which the obtained solution set approximates the true Pareto front. In contrast to the conventional Generational Distance (GD), which quantifies the average distance from solutions to the closest point on the true Pareto front, Inverted Generational Distance (IGD) assesses the average distance from the true Pareto front to the nearest point within the obtained solution set. Procedure for calculating IGD: Determine the Euclidean distance from each point on the true Pareto front to the closest point in the derived solution set. Calculate the mean of these distances. A smaller IGD value signifies that the solutions obtained are nearer to the true Pareto front, indicating superior performance.

Table.2. Mean inverted generational distance (IGD)

Problems	SPEA-II	NSGA-I	MOEA/D	NSGA-II	NSGA-III	MOABC	ABC-NSGAII
DCMO1	1.77E-01	2.29E-01	2.54E-01	1.10E-01	7.21E-01	1.28E-01	8.30E-02
DCMO2	7.31E-02	5.49E-02	5.49E-02	5.67E-02	7.64E-02	5.18E-02	7.03E-02
MTSOO1	8.50E+00	9.55E+00	**1.49E+01**	8.76E+00	1.63E+01	7.79E+00	**1.36E+01**
MTSOO2	**1.98E-01**	3.21E-01	5.07E-01	2.66E-01	8.58E-02	4.57E-01	**6.63E-02**
MTMOO1	6.61E-03	1.25E-02	3.23E-02	5.05E-03	**1.65E-02**	1.72E-02	**6.05E-03**
LSOP1	1.38E-02	1.87E-02	1.44E-02	4.74E-03	7.46E-03	1.80E-02	5.75E-03
LSOP2	1.05E-01	1.49E-01	1.68E-01	9.02E-02	7.83E-02	1.67E-01	8.30E-02
CMMO1	4.88E-02	5.82E-02	NaN	1.46E-01	NaN	NaN	4.60E-02
CMMO2	6.69E-02	9.41E-02	1.87E+00	1.13E-01	1.73E-01	3.33E+00	5.20E-02

4.1.3 Averaged Hausdorff Distance (Δ_p):

AHD quantifies the distance between two-point sets, specifically between the derived solution set and the actual Pareto front. The Hausdorff distance is defined as the maximum distance from any point in one set to the closest point in the other set. The AHD enhances this concept by averaging the maximum distances, resulting in a more balanced measure of similarity. Procedure for calculating AHD: Identify the nearest point on the true Pareto front for each point in the derived solution set and record the corresponding distance. Identify the nearest point in the obtained solution set for each point on the true Pareto front and record the distance. Calculate the mean of these distances. A reduced AHD signifies that the solution sets are more proximate and analogous, suggesting an improved approximation of the Pareto front.

Table.3. Mean averaged hausdorff distance (Δ_p)

Problems	SPEA-II	NSGA-I	MOEA/D	NSGA-II	NSGA-III	MOABC	ABC-NSGAII
DCMO1	2.77E-01	3.41E-01	3.34E-01	1.44E-01	4.94E+00	1.76E-01	**1.11E-01**
DCMO2	7.31E-02	5.49E-02	5.49E-02	5.67E-02	7.72E-02	5.18E-02	7.03E-02
MTSOO1	9.94E+00	1.14E+01	**1.83E+01**	9.99E+00	8.31E+01	9.58E+00	**1.87E+01**
MTSOO2	1.98E-01	3.21E-01	5.07E-01	2.66E-01	1.28E-01	4.57E-01	6.63E-02
MTMOO1	6.61E-03	1.25E-02	3.23E-02	5.05E-03	**1.70E-02**	1.80E-02	5.75E-03
LSOP1	**2.54E-02**	1.87E-02	1.54E-01	5.09E-03	7.46E-03	1.80E-02	5.75E-03
LSOP2	1.05E-01	1.49E-01	1.68E-01	9.02E-02	7.83E-02	1.67E-01	8.30E-02
CMMO1	5.54E-02	5.82E-02	NaN	1.46E-01	NaN	NaN	5.55E-02
CMMO2	6.69E-02	9.41E-02	1.89E+00	1.13E-01	2.70E-01	3.37E+00	5.20E-02

4.1.4 Spread:

It is utilised in multi-objective optimisation to evaluate the distribution and diversity of solutions along the Pareto front. This metric assesses the uniformity of solution distribution, thereby guaranteeing thorough representation of various trade-offs among objectives. This metric is derived from the Euclidean distances between consecutive solutions, reflecting the mean distance and its deviations, thereby offering insights into the uniformity of the solution distribution. In Many-Objective Optimal Power Flow (MOOPF), a low Spread Metric value signifies well-distributed solutions, essential for providing decision-makers with a wide and diverse array of optimal solutions.

Table.4. Mean Averaged spread metric

Problems	SPEA-II	NSGA-I	MOEA/D	NSGA-II	NSGA-III	MOABC	ABC-NSGAII
DCMO1	6.30E-01	6.38E-01	6.09E-01	3.28E-01	8.89E-01	8.66E-01	6.23E-01
DCMO2	**5.02E-01**	1.85E-01	1.72E-01	7.89E-02	3.86E-01	3.20E-01	5.10E-01
MTSOO1	9.17E-01	9.41E-01	7.88E-01	1.01E+00	**1.04E+00**	1.40E+00	**1.19E+00**
MTSOO2	5.25E-01	5.25E-01	7.92E-01	4.48E-01	4.82E-01	7.88E-01	5.00E-01
MTMOO1	5.16E-01	8.50E-01	1.76E+00	1.68E-01	4.61E-01	1.52E+00	4.94E-01
LSOP1	7.80E-01	1.32E+00	1.55E+00	2.01E-01	5.16E-01	1.59E+00	4.48E-01
LSOP2	4.90E-01	5.73E-01	**1.12E+00**	3.07E-01	5.03E-01	1.08E+00	5.09E-01
CMMO1	5.05E-01	5.60E-01	NaN	7.69E-01	NaN	NaN	4.60E-01
CMMO2	1.33E+00	1.17E+00	1.01E+00	1.04E+00	8.18E-01	1.00E+00	**1.36E+00**
DCMO1	7.42E-01	8.19E-01	6.10E-01	5.20E-01	**1.01E+00**	8.30E-01	5.61E-01
DCMO2	7.56E-01	8.99E-01	5.57E-01	NaN	NaN	NaN	NaN

Table.5. Overall Mean Friedman rank of all metrics combined

Problems	SPEA-II	NSGA-I	MOEA/D	NSGA-II	NSGA-III	MOABC	ABC-NSGAII
DCMO1	5.55	6.89	5.36	**1.93**	8.91	4.30	2.45
DCMO2	8.03	2.89	3.53	4.43	8.50	2.25	**1.47**
MTSOO1	3.44	4.38	5.13	4.15	4.31	**1.12**	3.13
MTSOO2	5.23	6.28	8.31	5.31	2.69	8.23	2.87
MTMOO1	3.24	4.90	9.00	**1.00**	5.65	6.86	**1.25**
LSOP1	4.60	5.59	8.63	**1.02**	3.08	5.77	**1.01**
LSOP2	4.78	7.08	8.48	2.13	2.14	**1.08**	2.57
CMMO1	**1.86**	2.96	6.00	4.27	6.00	6.00	**1.18**
CMMO2	3.50	4.34	6.82	4.12	4.74	6.58	2.72

4.2 DISCUSSION

Due to its improved convergence and Pareto front solution distribution, the hybrid approach combining Artificial Bee Colony (ABC) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) consistently outperforms other methods. Hypervolume (HV), Inverted Generational Distance (IGD), and Δp assess solution quality based on their proximity to the true Pareto front and distribution balance. ABC-NSGAII optimises convergence and solution diversity for complex multi-objective optimisation problems with statistically significant results. The clustering mechanism of HNSMOABC ensures well-distributed solutions in optimal regions, improving large-scale optimisation performance, but it may limit diversity at the Pareto front. MOEA/D-DAE algorithms excel at solution space exploration, as measured by diversity metrics like spread. The Friedman test shows ABC-NSGAII’s efficacy and reliability with a P-value of 0.016 and top metrics. Successfully solving IEEE-CEC 2023 benchmark problems shows its ability to manage complex trade-offs, constraints, and non-uniform Pareto fronts. Hybrid optimisation methods like ABC-NSGAII may outperform traditional and metaheuristic methods for multi-objective optimisation problems due to their balanced approach..

5. MULTI-OBJECTIVE OPTIMAL POWER FLOW

MOOPF, an advanced electrical power system optimisation problem, optimises multiple conflicting objectives, including generation costs, transmission losses, emissions, system security, and reliability. To solve MOOPF problems realistically, power balance, generator, voltage, and thermal constraints must be met. Power system operation and planning, renewable energy integration, and electricity market operations use MOOPF to ensure efficiency, reliability, and environmental friendliness. Advanced optimisation methods like hybrid MOABC and NSGA-II balance multiple objectives and handle complex optimisation landscapes to find high-quality solutions. MOOPF methodologies must be understood and applied to improve power system efficiency, reliability, and environmental sustainability.

6. IEEE 118 BUS SYSTEM DETAILS

The IEEE 118 Bus System is a commonly employed test case in power system research, depicting a portion of the American Electric Power System (AEP) in the Midwestern United States as of December 1962. The system consists of 118 buses, comprising 32 generator buses, 91 load buses, and 5 reference buses. The system comprises 19 generators with a total capacity of 4,377 MW, 177 transmission lines, 9 transformers and 35 synchronous condensers with a cumulative capacity of 574 MW. The system functions at a base voltage of 138 kV while serving 91 loads. Owing to its intricacy and authentic depiction of a power grid, it is frequently employed for the testing and validation of power flow algorithms, stability analyses, and optimisation methodologies.

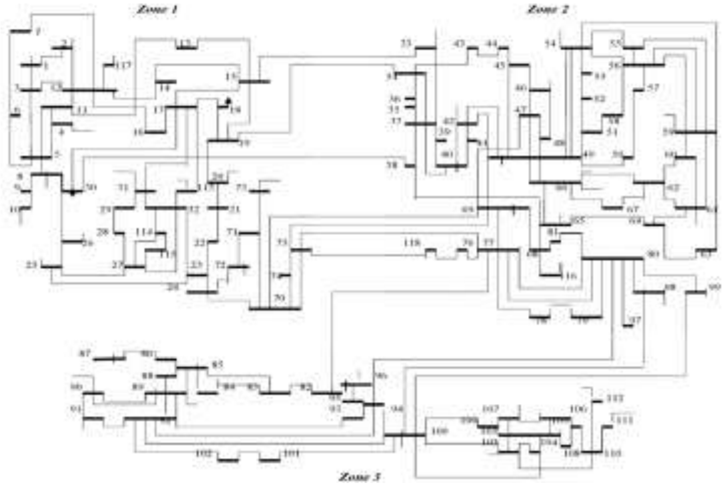

Fig.4. Single line diagram of IEEE 118-bus system

Fuel cost, active power loss, and voltage magnitude deviation parameters in Many-Objective Optimal Power Flow (MOOPF) must be studied for several reasons. First, reducing fuel costs boosts economic efficiency, lowering electricity prices and increasing utility profits. Second, reducing transmission line active power loss reduces energy waste and operational costs, improving system efficiency and reliability. Thirdly, voltage stability prevents malfunctions, device wear, and blackouts in electrical equipment and the power system. Fuel reduction also reduces greenhouse gas emissions, helping the environment. Optimised power flow ensures system reliability by meeting demand regardless of load conditions or faults. MOOPF balances economic, technical, and environmental goals to create a reliable and efficient power system.

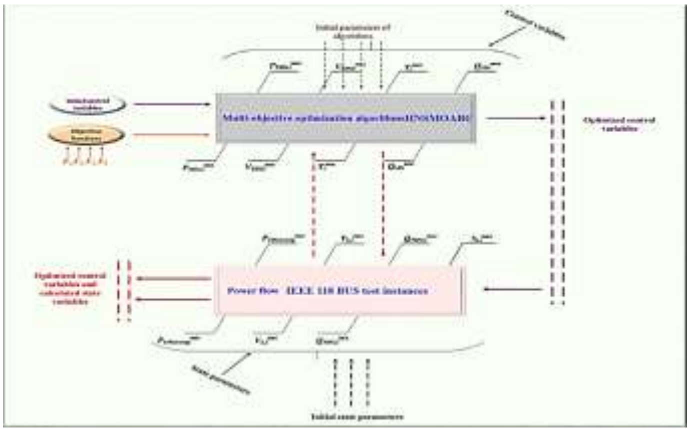

Fig.5. MOOPF Framework and mathematical formulations

6.1 CASE STUDY RESULT OF MOOPF PROBLEM ON IEEE 118 BUS SYSTEM

Mathematical formulations for MOOPF study [21] prime motive to optimal setting of control parameter at minimal thermal fuel cost, power loss and voltage deviation simultaneously so, the algorithm is run with three objective functions. The Pareto fronts (PFs) observed in this case are depicted in Fig.6. The comparison of the BCS values and the corresponding control variables obtained for Case-V is presented in Table.6.

The suggested algorithm obtains 137,715.17($/hr) fuel cost, 33.3462(MW) power loss, and 0.4779 (p.u) VMD, whereas NSGA-II [29] gives 138,441.48($/hr), 37.8479(MW), 0.5067(p.u) and MOABC [30] gives 138,501.58($/hr), 51.5057(MW), 0.5750(p.u), respectively. The bold values shown in the table are optimal objective values obtained using the proposed algorithm. The statistical inference including best, worst, range, standard deviation (SD) and mean values for the three cases of IEEE 118-bus power system is tabulated in Table.7. From the Table.8, it is evident that the suggested algorithm produces better performance as compared to NSGA-II [29] and MOABC [30] algorithms.

Table.6. Simulation result on Minimize objective functions in MOOPF 118 bus system

Sl. No	Control Variable	ABC-NSGAII	NSGA-II	MOABC	ABC-NSGAII	NSGA-II	MOABC
		Control Variables: Power (MW)			Control Variables: Voltage (p.u)		
1	1	49.8078	54.8971	23.8680	1.0116	1.0211	1.0285
2	4	52.5061	47.8583	23.5583	1.0034	1.0038	0.9910
3	6	37.9561	41.7676	30.3396	1.0186	1.0148	1.0380
4	8	40.4637	52.1134	68.8969	1.0130	1.0279	0.9943
5	10	208.3497	200.001	162.529	0.9954	1.0076	0.9799
6	12	96.2351	95.3491	94.2803	1.0202	1.0203	1.0032
7	15	59.9765	47.7239	41.3812	1.0114	1.0157	1.0131
8	18	44.6825	44.8845	87.9004	1.0142	1.0093	1.0188
9	19	46.3333	38.8888	55.6282	1.0155	1.0186	1.0374
10	24	23.7604	47.9193	47.9193	1.0165	1.0088	0.9903
11	25	117.6926	98.7580	71.8418	1.0118	1.0254	1.0193
12	26	154.555	165.6475	225.008	1.007	1.027	1.002
13	27	44.1010	41.2942	64.7284	1.0123	1.0192	1.0445
14	31	19.6902	24.6045	32.3143	1.0087	1.0082	1.0009
15	32	31.9930	35.9945	55.3926	1.0059	1.0105	0.9909
16	34	51.7709	52.5163	5.2702	1.0117	1.0189	0.9987
17	36	56.1834	41.0381	72.9698	1.0063	1.0057	1.0141
18	40	87.8627	58.5974	32.3235	1.0177	1.0058	1.0016
19	42	75.2689	56.1755	57.5625	1.0118	1.0127	1.0017
20	46	35.1325	49.1190	46.1951	1.0197	1.0145	1.0135
21	49	159.3047	167.186	206.595	0.9980	0.9970	0.9751
22	54	81.8220	78.8419	32.3143	1.0128	1.0080	1.0101
23	55	80.5026	64.8844	63.9898	1.0182	1.0245	1.0219
24	56	70.8324	61.9925	43.1943	1.0187	1.0313	1.0245
25	59	145.9911	151.241	161.442	1.0141	1.0241	1.0121
26	61	127.1395	136.523	109.375	1.0143	1.0338	0.9994
27	62	49.8338	37.0122	72.9286	1.0226	1.0071	0.9935
28	65	229.5327	222.242	256.717	1.0260	1.0103	0.9979
29	66	231.1206	244.556	211.476	0.9859	1.0170	1.0214
30	70	45.3337	38.0014	36.8410	1.0281	1.0108	1.0437
31	72	20.0243	40.2348	19.8350	1.0192	1.0070	1.0214
32	73	23.8761	37.2211	10.1501	1.0316	1.0343	0.9932
33	74	50.1527	47.4695	43.4136	1.0333	1.0054	1.0002
34	76	44.8794	55.6834	42.1826	1.0048	1.0170	0.9894
35	77	38.0621	35.9400	77.9524	1.0080	1.0240	0.9916
36	80	297.0032	255.412	217.792	1.0037	1.0097	1.0271
37	85	42.5265	45.5885	64.8361	1.0135	1.0109	1.0339
38	87	10.9515	6.4937	9.9615	1.0100	1.0115	0.9928

39	89	229.9336	243.088	227.022	1.0091	1.0288	1.0191
40	90	50.8835	58.2787	40.1591	1.0412	1.0245	1.0083
41	91	48.0809	51.0010	32.7856	1.0141	1.0221	1.0081
42	92	49.2068	45.5966	71.8462	1.0157	1.0237	0.9970
43	99	35.9029	49.0012	41.4485	1.0235	1.0129	1.0159
44	100	141.6298	126.013	165.347	1.0199	1.0172	1.0105
45	103	43.1302	49.2388	43.2952	1.0172	1.0221	1.0197
46	104	42.4401	44.8947	70.0230	1.0196	1.0164	1.0300
47	105	50.3917	36.2602	51.0041	1.0173	1.0239	1.0313
48	107	35.5470	37.5737	66.2487	1.0104	1.0056	1.0040
49	110	40.3137	52.1613	17.5272	1.0184	1.0045	0.9709
50	111	35.5358	44.9217	30.3810	1.0193	1.0173	1.0299
51	112	45.4344	47.0013	22.9620	1.0205	1.0225	1.0463
52	113	46.0275	43.1162	43.9970	1.0275	1.0312	1.0295
53	116	39.6684	43.9970	61.9924	1.0091	1.0051	1.0382

Table.7. Statistical Interference of IEEE 118 bus system.

Algorithms	Objectives	Best Value	Worst Value	Range	SD	Mean Value
Proposed ABC-NSGAII	**FC($/hr)**	**136,201.34**	**140,369.68**	**4,168.34**	**634.03**	**137,585.29**
	P_L(MW)	**30.3348**	**38.3905**	**8.0557**	**1.6158**	**33.7176**
	VD (p.u)	**0.4440**	**0.5951**	**0.1310**	**0.0247**	**0.5099**
NSGA-II [29]	**F_C($/hr)**	136,205.28	140,718.02	4,512.74	883.21	137,906.91
	P_L MW)	35.1875	44.5861	9.3986	2.1589	39.4477
	VD (p.u)	0.4556	0.7252	0.2795	0.0642	0.5653
MOABC [30]	**FC($/hr)**	136,253.94	141,933.91	5,679.97	1,528.17	138,618.22
	P_L (MW)	46.8119	82.3806	35.5687	8.6009	59.0408
	VD (p.u)	0.5192	0.8185	0.2993	0.0772	0.6320

Table.8. Performance Metric test on IEEE 118 MOOPF test system

Metric	Proposed ABC-NSGAII	NSGA-II [29]	MOABC [30]
IGD	**0.0812**	0.0962	0.5340
SP	**1.9159E8**	8.7203E7	3.2553E7

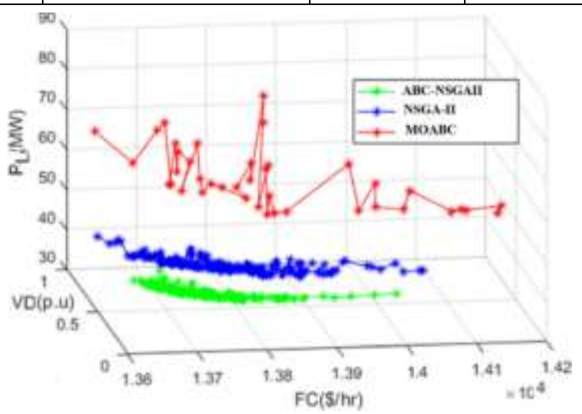

Fig.6. IEEE 118-bus power system Pareto Fronts (PFs) with three objectives

7. CONCLUSIONS

In this study, a novel non-dominated sorting hybrid Multiobjective artificial bee colony hybrid algorithm ABC-NSGAII was designed for solving multi-objective constraint optimization problems. To validate the proposed methods, standard test functions, such as the IEEE CEC 2023 suites were tested. By using statistical test measurement indices as Hypervolume, IGD, Hausdorff and spread metric, it gets, proposed algorithms is best result among recent metaheuristic algorithm. For real time computation analysis, further given problem studied as complex optimal power problem on IEEE 118 bus system. The multi-objective optimal power flow problem was solved as a multiobjective and multi-constrained optimization problem, where the cost, loss, and voltage deviation value were minimized. The obtained results show the Pareto optimal front obtained by Hybrid ABC-NSGAII was better than that of the existing literature. It was also observed that the proposed method can handle ramp rate limit constraints. The result shows that the proposed method is superb.

REFERENCES

[1] M. Balasubbareddy, "Multi-Objective Optimization in the Presence of Ramp-Rate Limits using Non-Dominated Sorting Hybrid Fruit Fly Algorithm", *Ain Shams Engineering Journal*, Vol. 7, No. 2, pp. 895-905, 2016.

[2] M. Balasubbareddy, S. Sivanagaraju and C.V. Suresh, "Multi-Objective Optimization in the Presence of Practical Constraints using Non-Dominated Sorting Hybrid Cuckoo Search Algorithm", *Engineering Science and Technology an International Journal*, Vol. 49, No. 4, pp. 603-615, 2015.

[3] G. Chen, X. Yi, Z. Zhang and H. Wang, "Applications of Multi-Objective Dimension-based Firefly Algorithm to Optimize the Power Losses, Emission and Cost in Power Systems", *Applied Soft Computing*, Vol. 68, pp. 322-342, 2018.

[4] J. Zhou, C. Wang, Y. Li, P. Wang, C. Li, P. Lu and L. Mo, "A Multi-Objective Multi-Population Ant Colony Optimization for Economic Emission Dispatch Considering Power System Security", *Applied Mathematical Modelling*, Vol. 45, pp. 684-704, 2017.

[5] M. Ding, H. Chen, N. Lin, S. Jing, F. Liu, X. Liang and W. Liu, "Dynamic Population Artificial Bee Colony Algorithm for Multi-Objective Optimal Power Flow", *Saudi Journal of Biological Sciences*, Vol. 24, pp. 703-710, 2017.

[6] S. Sahu, A.K. Barisal and A. Kaudi, "Multi-Objective Optimal Power Flow with DG Placement using TLBO and MIPSO: A Comparative Study", *Energy Procedia*, Vol. 117, pp. 236-243, 2017.

[7] L. Wu, Q. Liu, X. Tian, J. Zhang and W. Xiao, "A New Improved Fruit Fly Optimization Algorithm IAFOA and its Application to Solve Engineering Optimization Problems", *Knowledge-based Systems*, Vol. 144, pp. 153-173, 2018.

[8] L. Wang and X. Zheng, "A Knowledge-Guided Multi-Objective Fruit fly Optimization Algorithm for the Multi-Skill Resource-Constrained Project Scheduling Problem", *Swarm Evolutionary Computation*, Vol. 38, pp. 54-63, 2018.

[9] T.S. Du, X.T. Ke, J.G. Liao and Y.J. Shen, "DSLC-FOA: Improved Fruit Fly Optimization Algorithm for Application to Structural Engineering Design Optimization Problems", *Applied Mathematical Modelling*, Vol. 55, pp. 314-339, 2018.

[10] K. Nuaekaew, P. Artrit, N. Pholdee and S. Bureerat, "Optimal Reactive Power Dispatch Problem using a Two-

Archive Multi-Objective Grey Wolf Optimizer", *Expert Systems with Applications*, Vol. 87, pp. 79-89, 2017.

[11] M.J. Morshed, J.B. Hmida and A. Fekih, "A Probabilistic Multi-Objective Approach for Power Flow Optimization in Hybrid Wind-PVPEV Systems", *Applied Energy*, Vol. 211, pp. 1136-1149, 2018.

[12] S.K.M. Shareefa and R.S. Rao, "Optimal Reactive Power Dispatch Under Unbalanced Conditions using Hybrid Swarm Intelligence", *Computers and Electrical Engineering*, Vol. 69, pp. 183-193, 2018.

[13] W. Warid, H. Hizam, N. Mariun and N.I.A. Wahab, "A Novel Quasi-Oppositional Modified Jaya Algorithm for Multi-Objective Optimal Power Flow Solution", *Applied Soft Computing*, Vol. 65, pp. 360-373, 2018.

[14] A.F. Attia, R.A. El Sehiemya and H.M. Hasanien, "Optimal Power Flow Solution in Power Systems using a Novel Sine-Cosine Algorithm", *International Journal of Electrical Power and Energy Systems*, Vol. 99, pp. 331-343, 2018.

[15] G. Dhiman and V. Kumar, "Multi-Objective Spotted Hyena Optimizer: A Multi-Objective Optimization Algorithm for Engineering Problems", *Knowledge-based Systems*, Vol. 150, pp. 175-197, 2018.

[16] L. Lv and J. Zhao, "The Firefly Algorithm with Gaussian Disturbance and Local Search", *Journal of Signal Processing Systems*, Vol. 90, pp. 1123-1131, 2017.

[17] A.A.A. Mohamed, Y.S. Mohamed, A.A.M. EI-Gaafary and A.M. Hemeida, "Optimal Power Flow using Moth Swarm Algorithm", *Electric Power Systems Research*, Vol. 142, pp. 190-206, 2017.

[18] E. Davoodi, E. Babaei and B. Mohammadi-ivatloo, "An Efficient Covexified SDP Model for Multi-Objective Optimal Power Flow", *International Journal of Electrical Power and Energy Systems*, Vol. 102, pp. 254-264, 2018.

[19] A.A. El-Fergany and H.M. Hasanien, "Tree-Seed Algorithm for Solving Optimal Power Flow Problem in Large-Scale Power Systems Incorporating Validations and Comparisons", *Applied Soft Computing*, Vol. 64, pp. 307-316, 2018.

[20] E. Naderi, H. Narimani, M. Fathi and M.R. Narimani, "A Novel Fuzzy Adaptive Configuration of Particle Swarm Optimization to Solve Large-Scale Optimal Reactive Power Dispatch", *Applied Soft Computing*, Vol. 53, pp. 441-456, 2017.

[21] M. Sedighizadeh, M. Sarvi and E. Naderi, "Multi-Objective Optimal Power Flow with FACTS Devices using Shuffled Frog Leaping Algorithm", *International Review of Electrical Engineering*, Vol. 6, pp. 1794-1801, 2011.

[22] J. Wei, Y. Zhang, J. Wang, X. Caob and M.A. Khan, "Multi-Period Planning of Multi-Energy Microgrid with Multi-Type Uncertainties using Chance Constrained Information Gap Decision Method", *Applied Energy*, Vol. 260, pp. 1-6, 2020.

[23] A. Khan, H. Hizam, N.I. Abdul-Wahab and M.L. Othman, "Solution of Optimal Power Flow using Non-Dominated Sorting Multi Objective-based Hybrid Firefly and Particle Swarm Optimization Algorithm", *Energies*, Vol. 13,No. 16, pp. 1-7, 2020.

[24] N.C. Yang, D. Mehmood and K.Y. Lai, "Multi-Objective Artificial Bee Colony Algorithm with Minimum Manhattan Distance for Passive Power Filter Optimization Problems", *Mathematics*, Vol. 9, pp. 1-6, 2021.

[25] S. Subramanian, C. Sankaralingam, R.M. Elavarasan, R.R. Vijayaraghavan, K. Raju and L. Mihet-Popa, "An Evaluation on Wind Energy Potential using Multi-Objective Optimization based Non-Dominated Sorting Genetic Algorithm III", *Sustainability*, Vol. 13, No. 1, pp. 1-8, 2021.

[26] Z. Tong, J. Xin and C. Ling, "Many-Objective Hybrid Optimization Method for Impeller Profile Design of Low Specific Speed Centrifugal Pump in District Energy Systems", *Sustainability*, Vol. 13, pp. 1-9, 2021.

[27] M.Z. Islam, N.I.A. Wahab, V. Veerasamy, H. Hizam, N.F. Mailah, J.M. Guerrero and M.N.M. Nasir, "A Harris Hawks Optimization based Single- and Multi-Objective Optimal Power Flow Considering Environmental Emission", *Sustainability*, Vol. 12, pp. 1-8, 2020.

[28] T.T. Nguyen, "A High Performance Social Spider Optimization Algorithm for Optimal Power Flow Solution with Single Objective Optimization", *Energy*, Vol. 171, pp. 218-240, 2019.

[29] E. Naderi, M. Pourakbari-Kasmaei and H. Abdi, "An Efficient Particle Swarm Optimization Algorithm to Solve Optimal Power Flow Problem Integrated with FACTS Devices", *Applied Soft Computing*, Vol. 80, pp. 243-262, 2019.

[30] C.V. Suresh and S. Sivanagaraju, "Analysis and Effect of Multi-Fuel and Practical Constraints on Economic Load Dispatch in the Presence of Unified Power Flow Controller using UDTPSO", *Ain Shams Engineering Journal*, Vol. 6, pp. 803-817, 2015.

[31] M.A. Abido, "Optimal Power Flow using Tabu Search Algorithm", *Electric Power Components and Systems*, Vol. 30, pp. 469-483, 2002.

[32] R. Arul, G. Ravi and S. Velsami, "Non-Convex Economic Dispatch with Heuristic Load Patterns, Valve Point Loading Effect, Prohibited Operating Zones, Ramp-Rate Limits and Spinning Reserve Constraints using Harmony Search Algorithm", *Electrical Engineering*, Vol. 95, pp. 53-61, 2013.

[33] J. Zhu and J.A. Momoh, "Multi-Area Power Systems Economic Dispatch using Nonlinear Convex Network Flow Programming", *Electric Power Systems Research*, Vol. 59, pp. 13-20, 2001.

[34] T. Niknam, M.R. Narimani, J. Aghaei and R. Azizipanah-Abarghooee, "Improved Particle Swarm Optimisation for Multi-Objective Optimal Power Flow Considering the Cost, Loss, Emission and Voltage Stability Index", *IET Generation, Transmission and Distribution*, Vol. 6, No. 6, pp. 515-527, 2012.

[35] A.E. Chaib, H. Bouchekara, R. Mehasni and M.A. Abido, "Optimal Power Flow with Emission and Non-Smooth Cost Functions using Backtracking Search Optimization Algorithm", *International Journal of Electrical Power and Energy Systems, Vol.* 81, pp. 64-77, 2016.

[36] E. Naderi, M.P. Kasmaei, F.V. Cerna and M. Lehtonen, "A Novel Hybrid Self-Adaptive Heuristic Algorithm to Handle Single and Multi-Objective Optimal Power Flow Problems", *International Journal of Electrical Power and Energy Systems*, Vol. 125, pp. 1-6, 2021.

[37] P.K. Roy, S.P. Ghoshal and S.S. Thakur, "Optimal Power Flow using Biogeography based Optimization", *International Journal of Power and Energy Conversion*, Vol. 2, No. 3, pp. 216-249, 2010.

[38] M.S. Kumari and S. Maheswarapu, "Enhanced Genetic Algorithm based Computation Technique for Multi-Objective Optimal Power Flow Solution", *International Journal of Electrical Power and Energy Systems,* Vol. 32, pp. 736-742, 2010.

[39] C. Audet, J. Bigeon, D. Cartier, S. Le Digabel and L. Salomon, "Performance Indicators in Multiobjective Optimization", *European Journal of Operational Research*, Vol. 292, No. 2, pp. 397-422, 2021.

[40] Y. Tian, R. Cheng, X. Zhang and Y. Jin, "PlatEMO: A MATLAB Platform for Evolutionary Multi-Objective Optimization", *IEEE Computational Intelligence Magazine, Vol. 12, No. 4, pp. 73-87, 2017*.