Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, No.2, January : 2025

APPLICATION OF COMPUTATIONAL INTELLIGENCE FOR A MULTI-CRITERIA OPTIMAL POWER FLOW FRAMEWORK INCORPORATING AN IMPROVED NSGA-II USING ENHANCED AUGMENTED EPSILON CONSTRAINED HANDLING PROTOCOL

Abhishek Bajirao Katkar Lecturer, Electrical Engineering, Government Polytechnic, Kolhapur 416 004, Maharashtra, India email: er.abhishekkatkar@gmail.com,
(Prof.) Dr. Himmat Tukaram Jadhav Dean, Faculty of Science & Technology, SNDT Women's University, Mumbai, Maharashtra, India

ABSTRACT:
This paper presents an enhanced epsilon constraint-based Non-Dominated Sorting Genetic Algorithm II (EAEC-NSGAII) designed to tackle multi-objective optimal power flow (MOOPF) issues in electrical power networks. The proposed EAEC-NSGAII method integrates essential principles of the NSGA-II algorithm, incorporating novel features including improved epsilon constraint handling, nondominated sorting, crowding distance, and elite search strategies. The enhancements facilitate the generation of diverse nondominated solutions within a single iteration, while maintaining population diversity and ensuring effective constraint management. This approach employs a spread indicator to maintain a repository of the most recent nondominated solutions and utilises a fuzzy decision-making strategy to select a suitable solution from the nondominated set. The EAEC-NSGAII method's efficacy and scalability are evidenced by experiments conducted on the IEEE 30-bus system, which incorporates bi-objective and tri-objective optimisation multi-criteria framework. A comparative analysis with conventional NSGA-II and other state-of-the-art algorithms demonstrates that EAEC-NSGAII exhibits superior or comparable performance with reference to Augmented Epsilon Constraint NSGAII in addressing MOOPF problems, especially in managing constraints and attaining diverse, optimal solutions. The simulation results confirm the robustness and effectiveness of the proposed method in optimising cost, loss, and economic factors within the framework of techno-economic sustainability criteria. The EAEC-NSGAII algorithm is introduced as an effective and robust method for addressing complex multi-objective optimisation challenges in power systems.

Keywords:
Multi-objective Optimal Power Flow, Non-dominated Sorting Genetic Algorithm-II, Enhanced Augmenting Epsilon Constraint handling protocol, Emission pollution, Fuzzy decision maker, Constraints Pareto-dominance Approach

1. Introduction

The Optimal Power Flow (OPF) problem, first presented by Dommel and Tinney in the 1960s, is a critical element in the operation and control of power systems.[1] OPF aims to identify the optimal values for control variables to minimise a designated objective function, while complying with operational constraints that encompass both equality and inequality restrictions.[2] Initially, conventional optimisation methods, including linear programming (LP) and Newton's method, were utilised to address optimal power flow (OPF). [3]These methods encountered considerable difficulties in addressing nonlinear objective functions and constraints, which restricted their applicability to more complex systems. Heuristic and metaheuristic algorithms have emerged as effective alternatives to address the limitations of traditional methods, particularly in the context of multi-objective optimisation problems (MOOP). Techniques including Differential Evolution (DE)[5], Genetic Algorithm (GA)[6], Particle Swarm Optimisation (PSO)[7], Artificial Bee Colony (ABC)[8], Harmony Search (HS)[11], and Gravitational Search Algorithm (GSA)[12] demonstrate significant potential. These algorithms are effective in navigating extensive and intricate search spaces and can produce a varied array of Pareto-optimal solutions within a single computational execution, rendering them appropriate for multi-objective optimisation problems.

The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) has become prominent among evolutionary approaches due to its efficient non-dominated sorting process and its effectiveness in addressing multi-objective optimisation problems.[6] NSGA-II utilises crowding distance to preserve solution diversity and incorporates an elitist selection mechanism to facilitate convergence to optimal solutions. NSGA-II, while successful, faces limitations in tackling the specific challenges associated with Multi-Objective Optimal Power Flow (MOOPF), including the resolution of conflicts among objectives, the maintenance of solution diversity, and the prevention of premature convergence. This research introduces an enhanced algorithm, the Improved Non-Dominated Sorting Genetic Algorithm II (EAEC-NSGAII), aimed at effectively addressing MOOPF problems. This research presents several key innovations and contributions, including:

- Augmented Constraint Handling: EAEC-NSGAII presents an innovative epsilon constraint-handling mechanism that markedly improves solution accuracy and diversity.
- Efficient Sorting and Diversity Maintenance: The algorithm employs non-dominated sorting and crowding distance principles to effectively produce diverse sets of non-dominated solutions within a single iteration.
- Fuzzy Decision-Making: A fuzzy decision-making mechanism is utilised to determine the optimal compromise solution from the Pareto-optimal set, facilitating a balanced trade-off among competing objectives.
- An external archive is utilised to store and update the latest non-dominated solutions, thereby enhancing solution management efficiency.
- Innovative Trade-off Resolution: The newly proposed improved-augmented epsilon-constrained (EAEC) method is utilised to effectively and efficiently address complex trade-offs, demonstrating superior performance compared to traditional techniques like the weighted-sum method and standard NSGA-II.
- Enhanced constraint handling protocol: This strategy exhibits a superior ability to identify non-dominated solutions and acquire Pareto-efficient solution sets, effectively achieving balanced trade-offs among three primary objectives.

The proposed EAEC-NSGAII algorithm's efficacy is assessed utilising the IEEE 30-bus test system within bi-objective and tri-objective optimisation frameworks. Comparative analyses with advanced methods, such as NSGA-II and MODA, demonstrate the improved efficiency, scalability, and robustness of the proposed approach in addressing MOOPF challenges. This research advances multi-objective optimisation in power systems and highlights the practical relevance and applicability of the proposed EAEC-NSGAII method to complex real-world scenarios. The contributions establish a robust basis for tackling emerging challenges in contemporary power system optimisation.

2. Multiobjective optimal power flow framework: The optimal power flow (OPF) problem can be mathematically expressed as follows [12]:

$$min\ f(x,u) \tag{1}$$

$$to \begin{cases} g(x,u) = 0 \\ h(x,u) \leqslant 0 \end{cases} \tag{2}$$

In this context, f represents an objective, while x and u denote state and independent variables, respectively. Let g(x,u) and h(x,u) represent the equality and inequality constraints, respectively. This study includes several objective functions, with the formulation and corresponding constraints detailed below[9]:

<u>*Optimization of fuel cost (FC):*</u> The primary objective function in Optimal Power Flow (OPF) generally focusses on fuel cost, as expressed below[9].

$$f_1 = min\left(\sum_{m=1}^{ng}\left(a_m + b_m P_{gm} + c_k p_{gm}^2\right)\right) \tag{3}$$

Let f_1 represent the minimisation of fuel cost, where a_m, b_m, and c_m denote the cost coefficients of the m^{th} generator, and P_{gm} signifies the real power of the m^{th} generator.

Minimization of emission profile: The total tonnes per hour of atmospheric pollutants emitted, including sulphur and nitrogen oxides, from fossil fuel-fired units may be expressed as follows[9]:

$$f_2 = min\left(\sum_{m=1}^{ng}\left(\alpha_m + \beta_m P_{gm} + \gamma_m P_{gm}^2 + \mu_m exp\left(\xi_m P_{gm}\right)\right)\right) \tag{4}$$

where f_2 indicates emission released from the thermal power plant; $\alpha_m,\beta_m,\lambda_m,\mu_m,\xi_m$ denotes coefficients of m^{th} the unit, and these values depend on factors such as boiler type, operational parameters, and the type of fuel being utilized.

Minimization of active power loss (APL):The APL across all transmission lines can be mathematically expressed as the cumulative active power loss for each line, as detailed below:

$$f_3 = min\left(\sum_{m=1}^{ntl} G_m\left(V_n^2 + V_o^2 - 2V_n V_o \cos\theta_{no}\right)\right) \tag{5}$$

Where f_3 symbolizes minimization of APL; Gm represents the conductance of m^{th} the bus; V_n,V_o signifies voltages of n^{th} &o^{th} buses individually.

Constraints: The multiobjective optimisation optimal power flow (MOOPF) problem is limited by numerous system requirements, including all the constraints listed below:

Equality constraints

The equality constraints in OPF represent the essential physical principles that regulate the power system. These constraints are expressed through the subsequent equations:

$$P_{gm} - P_{dm} - V_m \sum_{m=1}^{nb} V_n\left(G_{mn}\cos\theta_{mn} + B_{mn}\sin\theta_{mn}\right) = 0 \tag{6}$$

$$Q_{gm} - Q_{dm} - V_m \sum_{m=1}^{nb} V_n\left(G_{mn}\sin\theta_{mn} - B_{mn}\cos\theta_{mn}\right) = 0 \tag{7}$$

where P_{gk},Q_{gk},P_{dk},Q_{dk} signifies real and reactive power generations and loads at k^{th} bus respectively; G_{mn}&B_{mn} indicates the conductance and susceptance among m^{th}&n^{th} buses individually.

Inequality constraints:The inequality constraints define the allowable range for variables, ensuring they stay within feasible limits as specified below;

$$\begin{cases} P_{gm}^{min} \leqslant P_{gm} \leqslant P_{gm}^{max} \\ V_{gm}^{min} \leqslant V_{gm} \leqslant V_{gm}^{max} \quad m = 1,2,\ldots,ng \\ Q_{gm}^{min} \leqslant Q_{gm} \leqslant Q_{gm}^{max} \end{cases} \tag{8}$$

where, P^{min}_{gm},P^{max}_{gm},V^{min}_{gm},V^{max}_{gm},Q^{min}_{gm}&Q^{max}_{gm} signifies low and high values of real power, voltages, and reactive power limits of m^{th} generator respectively, P_{gm},V_{gm}&Q_{gm} symbolizes real power, voltage, and reactive power of m^{th} generator respectively.

3. Non-Dominated Sorting Genetic Algorithm-II

It was initially proposed by Deb et al. [1] in the year 2000 in `International Conference on Parallel Problem Solving from Nature.' Single-objective optimisation algorithms can be readily compared through objective values or computational durations. In multi-objective optimisation algorithms, if the objective values of one algorithm surpass those of another across all objectives, a comparison can be made based on these objective values. Nonetheless, comparing the non-dominated sets of near-optimal solutions derived from multi-objective optimisation algorithms proves challenging. The Non-Dominated Sorting Genetic Algorithm (NSGA-II) is an effective decision space exploration tool derived from Genetic Algorithms (GA) for addressing Multi-objective Optimisation Problems (MOOPs). NSGA-II is an enhanced iteration of the non-dominated sorting genetic algorithm (NSGA-II) [21], which has faced criticism from researchers for its shortcomings, including the lack of elitism, the necessity to establish a sharing parameter for diversity maintenance, and its considerable computational complexity. Conversely, the NSGA-II design incorporates elitism and does not require a sharing parameter. It employs the crowding distance operator for the purpose of diversity preservation.

*3.1. Basic Structure of NSGA-II:*The NSGA-II philosophy is founded on four principal tenets: Non-Dominated Sorting, Elite Preserving Operator, Crowding Distance, and Selection Operator. The following subsections provide a concise description of these topics.

3.2. Non-dominated sorting: The population members are organised according to the principle of Pareto dominance. The non-dominated sorting process commences by assigning the initial rank to the non-dominated individuals within the original population. The highest-ranked members are subsequently positioned at the forefront and eliminated from the original population. Subsequently, the non-dominating sorting procedure is executed on the remaining members of the population. The non-dominated individuals of the remaining population are assigned the second rank and positioned in the second front. A multi-objective problem encompasses multiple objective functions, rendering it impossible to rank individuals in a population solely based on their objective function values. To achieve uniformly distributed nondominated solutions, crowding distance calculations and rapid nondominated sorting [44] are utilised to establish a ranking methodology for solutions within a multiobjective framework. This process persists until all members of the population are positioned on distinct fronts based on their ranks, as illustrated in Fig. 1.

*3.3. Elite Preserving Operator:*The elite preservation strategy maintains the superior solutions of a population by directly transferring them to subsequent generations. The non-dominated solutions identified in each generation progress to subsequent generations until they are surpassed by dominant solutions.

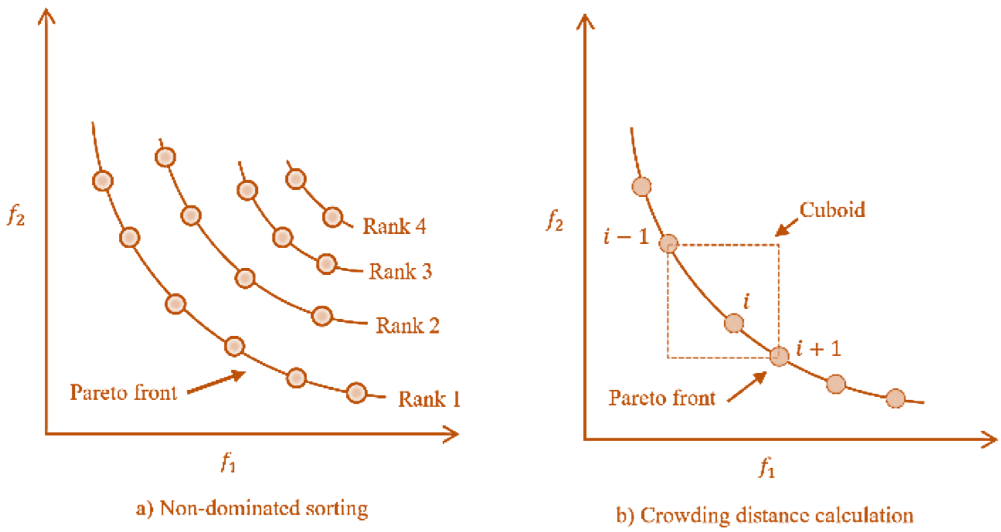

Fig 1.: Non-dominated sorting procedure and Crowding distance calculation.

3.4. Crowding distance: The crowding distance is calculated to estimate the density of solutions surrounding a particular solution. It is the aver- age distance of two solutions on either side of the solution along each of the objectives. On comparing two solutions with different crowding distances, the solution with the largecrowded distance is considered to be present in a less crowded region. If f^i is the j^{th} value of an objective function for the i^{th} individual and, $f^{\max}$ and $f^{\min}$ are the maximum and minimum values respectively of j^{th} objective function among all the individuals. Then, the crowding distance of i^{th} individual is defined as the average distance of two nearest solutions on either side, as given in (9)

$$cd(i) = \sum_{i=1}^{k} \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{\max} - f_j^{\min}} \tag{9}$$

where k is the number of objective functions.

3.5. Selection operator: After the crowding distance and fast nondominated sorting approaches have been completed, each individual has two qualities: crowding distance (cd) and nondominated rank (r). To obtain a uniformly spread Pareto optimal front, the crowded-comparison operator (φ_n) is used to compare the two solutions in a multi-objective space as follows [44], [45]:

$$i \ \varphi_n \ j \text{ if } (r_i < r_j) \text{ or } ((r_i = r_j) \text{ and } (cd_i > cd_j)) \tag{10}$$

When two solutions occupy distinct nondominated ranks, the solution with the superior rank is favoured. If both solutions possess the same rank, the solution with a superior crowding distance value is favoured. Consequently, the crowded comparison operator offers a ranking mechanism to organise individuals within a multi-objective space. The subsequent generation's population is chosen utilising a crowded tournament selection operator, which employs the ranks of the population members and their crowding distances for selection purposes. The criterion for choosing one individual from two population members for the subsequent generation is-

i) If both the population members are of different ranks, then the one with the better rank is selected for the next generation
ii) If both the population members are of the same ranks, then the one with the higher crowding distance is selected for the next generation

4. Concept of Pareto Dominance Approach

A multiobjective evolutionary algorithm, such as NSGA-II, yields a collection of compromised optimal solutions upon resolving a multiobjective optimisation problem (MOOP). Decision-makers utilise preference information to select the optimal compromised solution from the array of available compromised solutions. Numerous methodologies utilising MCDM fuzzy analysis, along with additional criteria, are employed to identify the optimal compromised solution in the reviewed literature.

Let x^1 and x^2 be the two feasible solutions of the multiobjective minimization problem (1). The solution x^1 can be viewed as better than x^2 if the following conditions hold:

1. $f_j(x^1) \le f_j(x^2)$ for all $j = \{1, 2, \ldots, k\}$
2. $f_j(x^1) < f_j(x^2)$ for at least one $j = \{1, 2, \ldots, k\}$

where k is the number of objective functions, $f_j(x)$ is the j^{th} value of an objective function for decision vector x. In this case, we say that x^1 dominates x^2 (or x^2 is dominated by x^1): x^1 is better than x^2. The relation '<' (or '>' for maximiza- tion problem) can be denoted as a dominance operator Δ. $x^1 \Delta x^2$ represents x^1 dominates x^2. When a solution x of (1) is not dominated by any other feasible solutions, it is called a Pareto optimal solution. The set of all Pareto optimal solutions are referred to as a Pareto set. The objective vector corresponding to the Pareto set is defined as a Pareto front, as shown in Fig. 2.

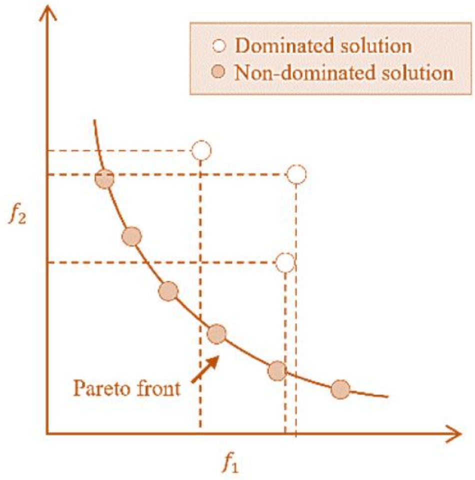

Fig 2: Constraint Pareto-dominance Approach methodology

In the literature, NSGA-II algorithms are compared to state-of-the-art algorithms to assess their efficacy. They compare algorithm solutions for convergence and diversity. Researchers compared algorithm efficiency using computational time. This study uses objective function values and computational time as performance metrics. NSGA-II's performance has been measured using many metrics, including initialisation, selection scheme, crossover and mutation operators, crowding distance operator, constraint handling technique, and others. The proposed method uses the enhanced Augmented Epsilon-Constrained (EAEC) method to balance multiple objectives, unlike previous models. Innovative acceleration mechanisms improve computational efficiency and generate high-quality non-dominated solutions in this method. Key contributions and features of the method are listed below:

- Enhanced Computational Efficiency: The EAEC method improves convergence speed without compromising solution quality by incorporating early loop exits and bouncing step adjustments, boosting the conventional epsilon-constrained approach. It generates diverse and accurate Pareto frontiers better than NSGA-II and weighted sum methods, according to comparative studies.
- Diversity Maintenance Archive: The method uses an internal archive to retain diverse Pareto front solutions. This mechanism balances diversity and accuracy, giving decision-makers many trade-offs between conflicting goals.
- Faster and Precise Non-Dominated Solution Identification: EAEC method reduces computational overhead by using Pseudo-Nadir points to approximate feasible solutions. Solution quality and computational time are better than NSGA-II and scalarization methods, making it ideal for complex multi-objective optimisation problems.

5. Concept of the Enhanced Epsilon-Constraint Method

The epsilon-constraint method, foundational to EAEC, reformulates a multi-objective optimisation problem by designating one objective as the primary function for minimisation or maximisation. Transforming remaining objectives into constraints by applying upper bounds (or lower bounds for maximisation). The bounds are denoted by ϵ, which delineates the satisfaction levels for these objectives. The variation in epsilon values defines the feasible solution space and aids in identifying Pareto-optimal solutions. The Pareto front illustrates the trade-offs among objectives. The significance of ϵ values in delineating the feasible criterion space and directing solution selection. The epsilon-constraint method can be expressed mathematically as follows:

$$\text{Minimize } f_1(\mathbf{x}) \quad \text{subject to: } \quad f_i(\mathbf{x}) \leq \epsilon_i, \; \forall i \neq 1.$$

The Enhanced Epsilon-Constraint Method's strengths lie in its ability to generate non-extreme efficient solutions, which are crucial for examining trade-offs between objectives. The iterative process facilitates a thorough examination of trade-offs through the systematic variation of epsilon values.

Advancements in EAEC involve augmentation mechanisms that incorporate pseudo-nadir points to approximate feasible solutions and enhance computational efficiency. Utilises acceleration methods such as early loop exit and adaptive modifications to bounding steps. EAEC demonstrates superior accuracy in identifying Pareto-optimal solutions when compared to NSGA-II and weighted sum methods.

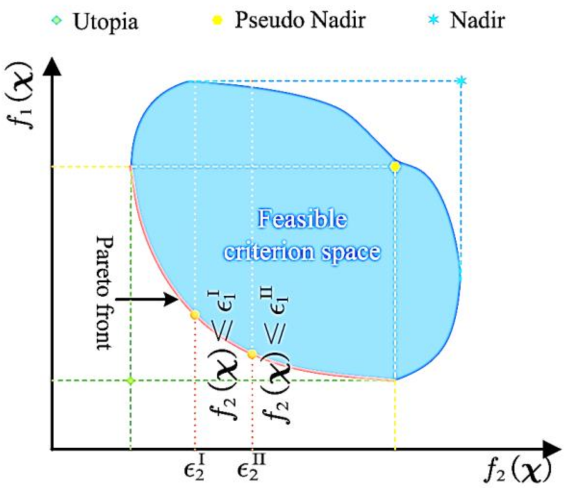

Fig.3 : Graphical Representation of EAEC Convergence to Pareto Optimal Solutions in MOO Problem

The method results in an expanded distribution along the Pareto front, providing a wider array of trade-offs for decision-makers. Although the weighted sum approach is more efficient, EAEC notably decreases computation time in comparison to traditional AEC by utilising the suggested acceleration mechanisms.

Figure 3 in the original study illustrates that the EAEC method exhibits faster convergence rates to Pareto-optimal solutions than AEC, NSGA-II, and weighted sum methods. The introduction of Pseudo-Nadir points facilitates accurate estimation of solution ranges, reduces redundant computations, and maintains equality within feasibility bounds. This method facilitates effective exploration of solution spaces while maintaining a balance between computational time and solution quality. The EAEC method serves as a strong alternative for situations that demand high-quality solutions while utilising limited computational resources. The integration of efficiency-enhancing mechanisms with the epsilon-constrained approach achieves a balance among solution diversity, accuracy, and computational time. Its application in engineering optimisation problems characterised by strict time constraints and multiple objective trade-offs represents a significant contribution to the field.

6. Pseudocode for NSGA-II with Improved Augmented Epsilon-Constrained Method

This pseudocode integrates NSGA-II with the Enhanced Epsilon-Constrained Method (EAEC) to handle multi-objective optimization problems while improving computational efficiency. Algorithm: NSGA-II with Improved Augmented Epsilon-Constrained Method

Input:

Population size (N)
Maximum generations (G)
Multi-objective functions (F = {f1(x), f2(x), ..., fm(x)})
Decision variable bounds (X)
Epsilon values for constraints (ε)

Output:

Pareto-optimal solutions (P*)

1. Initialize:

a. Generate an initial random population P0 of size N.

b. Evaluate objective functions F for each individual in P0.
c. Create a payoff matrix Φ using EAEC to calculate Utopia and Pseudo Nadir points.
d. Set ε values for each objective based on Φ.
2. Begin Generational Loop (generation = 1 to G):
a. Combine parent population (Pt) and offspring population (Qt) into Rt:
$Rt = P_t \cup Qt$
b. Non-dominated Sorting:
- Perform non-dominated sorting on Rt.
- Divide Rt into multiple non-dominated fronts (F1, F2, ..., Fk).
c. Crowding Distance Assignment:
- For each front Fi, calculate crowding distances for all individuals.
d. Select N individuals for the new population Pt+1:
- Add individuals from fronts Fi (starting from F1) until Pt+1 reaches size N.
- If adding a full front exceeds N, use crowding distance to select remaining individuals.
e. Apply Genetic Operators:
- Selection: Select parents using tournament selection based on rank and crowding distance.
- Crossover: Perform crossover to generate offspring.
- Mutation: Apply mutation to introduce diversity.
- Generate offspring population Qt.
f. Epsilon-Constrained Evaluation with EAEC:
- For each individual in Qt:
i. Replace Nadir points with Pseudo Nadir points to calculate objective ranges.
ii. Apply EAEC constraints using the modified objective ranges:
- Minimize the augmented objective function, replacing slack variables with normalized objective ranges.
- Penalize infeasible solutions.
iii. Apply early exit from loops when infeasibility is detected.
iv. Implement bouncing step mechanism to accelerate convergence:
- Adjust loop-control variables to skip redundant evaluations and improve search efficiency.
g. Update Payoff Matrix:
- Update Φ using new solutions to refine Utopia and Pseudo Nadir points.
- Dynamically adjust ε values based on updated Φ.
3. End Generational Loop.
4. Return Final Pareto-Optimal Solutions:
- Collect all non-dominated solutions from the final population Pt into P*.

The primary characteristics integrate the NSGA-II framework with the EAEC method to improve multi-objective optimisation. NSGA-II employs non-dominated sorting, crowding distance, and genetic operators, including selection, crossover, and mutation, to sustain diversity and facilitate exploration. EAEC employs Pseudo Nadir points to achieve tighter bounds and enhances constraints through normalised objective ranges. It imposes penalties on infeasible solutions and guarantees efficient convergence. Efficiency mechanisms encompass early exit strategies to minimise superfluous computations and bouncing steps to enhance convergence speed. The dynamic adjustment of Utopia and Pseudo Nadir points, along with ε values, enhances the search for efficient solutions, providing a strong methodology for addressing complex multi-objective optimisation problems.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, No.2, January : 2025

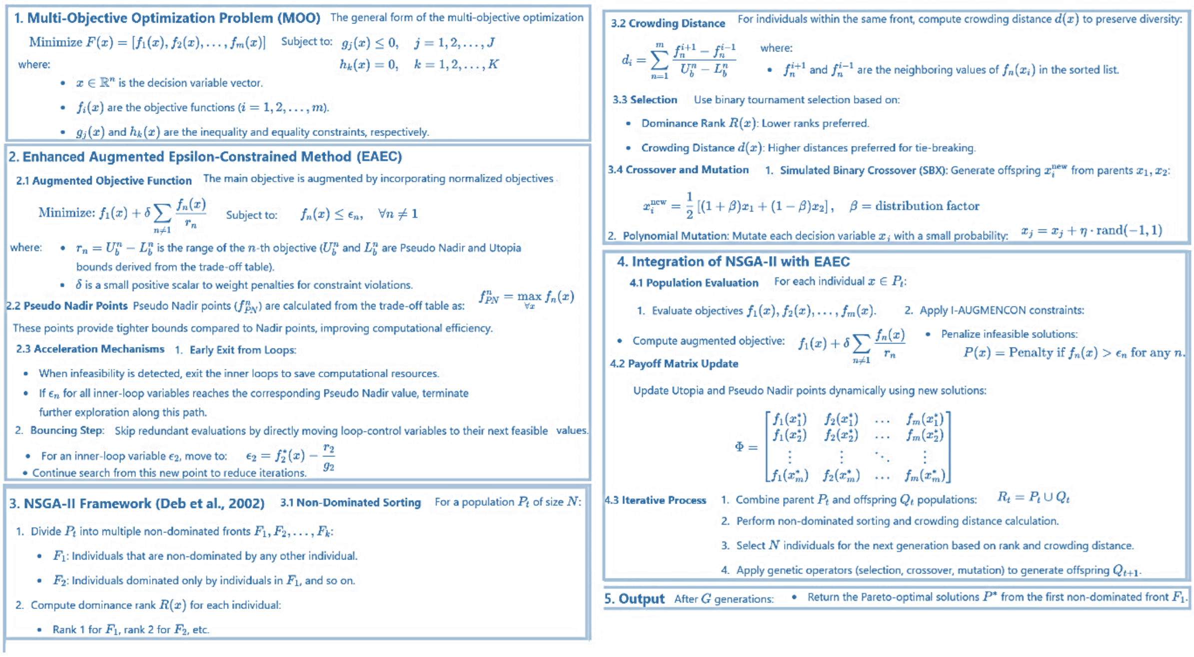

Fig.4: Schematic work-flow of EAEC based EAEC-NSGAII

The combination of the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and the Enhanced Augmented Epsilon-Constrained Method (EAEC) establishes a strong framework for tackling complex multi-objective optimisation problems (MOOP). NSGA-II utilises non-dominated sorting, crowding distance, and evolutionary operators to produce a variety of Pareto-optimal solutions, whereas EAEC improves constraint management via dynamic and adaptive mechanisms. EAEC substitutes conventional Nadir points with dynamically updated Pseudo Nadir points obtained from a trade-off table, thereby providing more precise and applicable bounds. EAEC systematically penalises constraint violations through the normalisation of objective ranges, eliminating the need for manually tuned parameters. Significant innovations encompass early loop exits to minimise computation time, bouncing steps to avoid redundant evaluations, and a dynamic payoff matrix to enhance constraints over generations. These features facilitate a balanced trade-off between exploration and exploitation, resulting in high-quality Pareto fronts. In comparison to conventional methods such as Superiority of Feasible Solutions (SF), Self-Adaptive Penalty (SP), and ε-Constraint (EC), EAEC demonstrates enhanced accuracy, efficiency, and adaptability, eliminating the need for parameter tuning and the inefficiencies linked to stochastic approaches like Stochastic Ranking (SR). EAEC outperforms Constraint-Domination Principles and Adaptive Trade-off Models (ATM) in large-scale, constraint-dominated problems by enhancing computational efficiency and solution quality. The integration of NSGA-II and EAEC yields comprehensive, high-quality Pareto-optimal solutions, establishing it as a vital method for real-world multi-objective optimisation contexts where accuracy, scalability, and computational efficiency are essential.

7. Modeling and Simulation of EAEC based NSGAII for MOOPF Framework:

The EAEC-NSGAII technique is presented for addressing multiobjective optimal power flow (MOOPF) issues. EAEC-NSGAII initially modifies the population to address MOOPF challenges. Furthermore, it utilises a specialised archive to preserve nondominated solutions obtained throughout the evolutionary process. A fuzzy decision technique is employed to obtain the best compromise solution (BCS) from the archive set. The procedural steps for the EAEC-NSGAII technique to address MOOPF issues are delineated as follows:

7.1 Initialization: EAEC-NSGAII, each population is considered a solution that is generated arbitrarily during the initialisation phase. The complete feasible search space for the EAEC-NSGAII technique, which includes colliding bodies, is presented as follows:

$$X = \begin{bmatrix} P_{g1,2},\ldots,P_{g1,ng},V_{g1,1},\ldots,V_{g1,ng},t_{1,1},\ldots,t_{1,nt},b_{sh1,1},\ldots b_{sh1,nc} \\ \vdots \\ P_{gm,2},\ldots,P_{gm,ng},V_{gm,1},\ldots,V_{gm,ng},t_{m,1},\ldots,t_{m,nt},b_{shm,1},\ldots b_{shm,nc} \\ \vdots \\ P_{gN,2},\ldots,P_{gN,ng},V_{gN,1},\ldots,V_{gN,ng},t_{N,1},\ldots,t_{N,nt},b_{shN,1},\ldots b_{shN,nc} \end{bmatrix} \quad (10)$$

7.2 Nondominated sorting process: The EAEC-NSGAII framework begins by initializing the CDs (candidate solutions) population using Eq. (10). To classify the CDs into different non-dominated layers, the following steps are performed:

1. **Domination Assessment**: Each CD evaluates all objectives and determines two factors: (i) the domination count n_p, which is the number of solutions that dominate the given CD_p, and (ii) S_p, the set of solutions dominated by *p*. All solutions in the first non-dominated (ND) layer have a domination count of zero.
2. **First ND Layer**: Solutions with zero domination count form the Pareto-optimal front, assigned a rank of 1.
3. **Subsequent Layers**: For each solution ppp in the current ND layer, the domination count of all solutions in S_p is decreased by 1. If a solution's domination count becomes zero, it is moved to the next ND layer and assigned a rank of 2.
4. **Iteration**: This process is repeated for all CDs in subsequent layers until all non-dominated levels are identified.

7.3 Update an external archive: Preference is accorded to superior CDs with lower ranks during selection. In cases where multiple candidate solutions share the same rank, those exhibiting greater crowding distances are given priority, thereby enhancing diversity. The systematic approach enables EAEC-NSGAII to comprehensively investigate the search space while preserving optimal solutions throughout iterations. The principle of Pareto dominance regulates the updating process of the archive set. If a particular CD in the search area is surpassed by any member of the archive, it is excluded from the archive. If an individual surpasses one or more members of the archive and is included in the archive cluster, the outperformed candidate solutions are removed. If external members surpass the extreme archive, the most densely populated region is chosen for removal, and a spread indicator is implemented to manage the archive length. Additionally, the crowding distance procedure is utilised to determine the ranking of various layers, as detailed below.

$$cd_{s,r} = \sqrt{\sum_{m=1}^{MO} \left(cd_{s,r}^{m}\right)^2};\ \ r = 1,2,\ldots,Al;\ \ cd_{s,r}^{m} = fit_{r+1}^{m} - fit_{r-1}^{m} \quad (11)$$

$$SI = \sum_{\substack{r=1 \\ r\neq E_p}}^{Al} \left|cd_{s,r} - \overline{cd}_s\right| / (Al - MO) \times \overline{cd}_s \quad (12)$$

where $cd_{s,r}$ denotes crowding distance, MO expresses total number of objectives, Al is the elite external archive length, $fit^{m}{}_{r+1}, fit^{m}{}_{r-1}$ are the m^{th} fitness of $(r+1)^{th}$&$(r-1)^{th}$ points. *SI* indicates the spread indicator.

7.4 The definition of CD population: The literature indicates that the classical technique is inadequate for solving MOOPF problems. This limitation is derived from Eq. (15), in which the mass of each population (CD) represents the fitness value of an individual objective. MOOPF problems involve multiple objectives, requiring adjustments to CD to address these conflicting goals. The calculation of mass for multiple objectives is complex due to the necessity of simultaneously considering various fitness values, which presents challenges related to normalisation and aggregation. Each objective may possess varying scales and units, complicating direct comparisons. Normalisation of the fitness values

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, No.2, January : 2025

for all objectives is necessary, necessitating further calculations to create a unified scale. After normalisation, the values are aggregated to ascertain the mass of each body. This introduces additional complexity, as it necessitates identifying an appropriate method for combining the normalised values to accurately represent the trade-offs among the conflicting objectives. The aggregation process requires careful design to ensure that the resulting mass representation accurately reflects the nuances of the multiobjective optimisation problem, as detailed in [30].

$$M_g = \sum_{h=1}^{M} \left(m_g^h\right)^2 \Big/ \sum_{u=1}^{N} \sum_{v=1}^{M} \left(m_v^u\right)^2 \tag{23}$$

$$m_v^u = \frac{F_v^u - worst^u}{best^u - worst^u} \quad u = 1, 2, \ldots, M \tag{24}$$

where M_g shows mass of g^{th} CD; $m^u{}_v$ denotes normalized fitness value; $worst^u$,$best^u$ indicate represent worst and best fitness values in all the CDs of u^{th} objective.

7.5 Update positions of CDs with changed crossover: As a result of the updated velocities, all the CDs are adjusted as follows:

$$M_g = \sum_{h=1}^{M} \left(m_g^h\right)^2 \Big/ \sum_{u=1}^{N} \sum_{v=1}^{M} \left(m_v^u\right)^2 \tag{13}$$

$$m_v^u = \frac{F_v^u - worst^u}{best^u - worst^u} \quad u = 1, 2, \ldots, M \tag{14}$$

where $X^{J+1}{}_m$,$X^J{}_m$ indicate positions of m^{th} CD in $(m+1)^{th}$&m^{th} iterations; and NCV denotes number of control variables.

7.6 Elite archive updating procedure: The forthcoming generation's candidate solutions consist of the optimal solution endpoints within the external archive, strategically located in the least congested area. Preserving elite CDs improves performance and protects against the loss of valuable solutions. A random selection of a percentage of CDs from the archive is included in the CDs list. The total number of bodies is subsequently limited by removing the least affluent crossover operator, starting from the previous layer of the ND sorting populations.

7.7 Fuzzy decision-making technique: In multi-objective optimisation with Pareto front considerations, the goal is to identify non-dominated solutions. A solution is deemed nondominated if enhancing one objective function necessitates a trade-off with another. The methodologies used to address these issues differ in two primary dimensions: (i) the strategy for generating the nondominated solution set, and (ii) the manner of interaction with decision-makers, encompassing the nature of information shared, including trade-offs. The selection of the BCS from the trade-offs is essential in the decision-making process. In conclusion, a fuzzy decision procedure is employed to achieve a suitable and optimal compromise solution from the non-dominated set. The membership The function μ(fp) is independently determined by analysing the lower and upper values of each objective, as well as the rate of satisfaction increase outlined in [30].

$$\mu\left(f_p\right) = \begin{cases} 1 & f_p \leqslant f_p^{min} \\ \dfrac{f_p^{max} - f_p}{f_p^{max} - f_p^{min}} & f_p^{min} < f_p < f_p^{max} \\ 0 & f_p \geqslant f_p^{max} \end{cases} \tag{15}$$

The values of the membership function reflect the extent to which a nondominated solution meets the fp objectives, quantified on a scale from 0 to 1. The evaluation of each solution's effectiveness in meeting the objectives is achieved by assessing the sum of membership function values ($\mu(fp)$; $i=1,2,...,MO$) across all objective functions. The performance of each ND solution can be evaluated against others by normalising its values in relation to the total sum, as outlined below:

$$\mu_D^q = \left[\sum_{p=1}^{MO} \mu\left(f_p^q\right)\right] \Big/ \left[\sum_{q=1}^{ND}\sum_{p=1}^{MO} \mu\left(f_p^q\right)\right] \tag{16}$$

where μ^q_D indicates normalized membership function within a fuzzy set; The solution achieving the highest normalized membership μ^q_D within the fuzzy set max$\{\mu^q_D; q=1,2,...,ND\}$ should be selected as the BCS.

8. EAEC-NSGAII Algorithm workflow for multiobjective OPF Problem:

The computational framework of the proposed EAEC-NSGAII methods, accompanied by detailed procedural guidelines and the flowchart depicted in Fig. 5, for tackling MOOPF issues, is presented as follows:

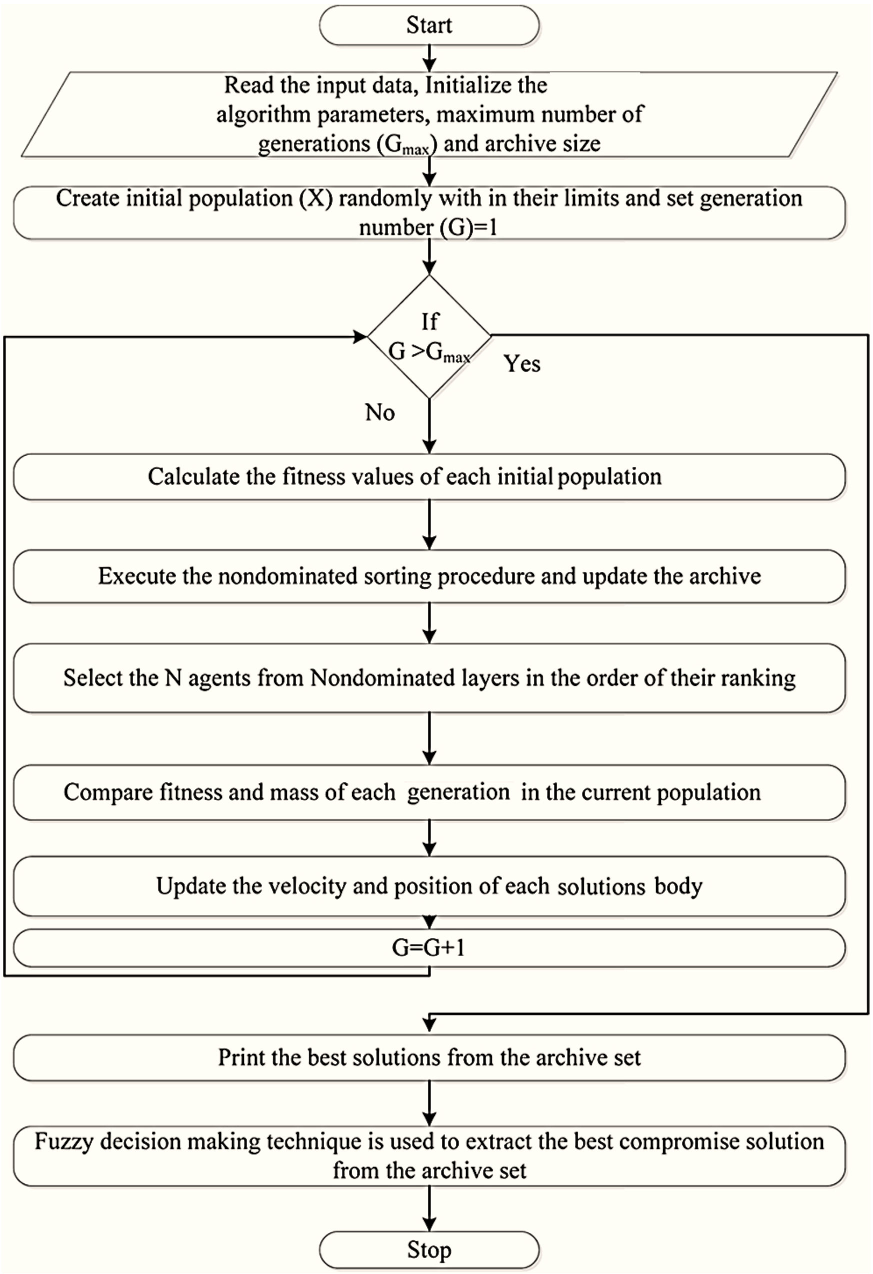

Fig. 5: Flowchart of EAEC-NSGAII approach for MOOPF problems.

Step 1: Define the parameters for EAEC-NSGAII, including the number of candidate solutions (NCD), archive size (A), and maximum iteration count (I_{max}).
Step 2: Initialisation. Generate each candidate solution, indicating a potential resolution of an objective function with randomly generated constraint variables.
Step 3. The fitness value of each CD is evaluated as follows:

$$|F| = f_j + w_P\left(|P_{g1} - P_{g1}^{lim}|\right)^2 + w_V\left(|V_l - V_l^{lim}|\right)^2 + w_Q\left(|Q_g - Q_g^{lim}|\right)^2 + w_S\left(|S_l - S_l^{lim}|\right)^2 \quad (17)$$

Step 4. Execute the NS process and store all identified nondominated CDs X in the archive set, followed by an appropriate update.
Step 5: Ascertain the mass value of each CD Assess the velocities of these groups prior to collision.
Step 6. Following the movement of the population (CDs) trailing the stationary CDs, update the velocities of the CDs subsequent to the collision event.
Step 7. If the maximum generation has not been achieved, return to Step 3; otherwise, present the ND solution in the external archive.
Step 8. Employ the fuzzy method to derive the BCS from the ND solution set.

9. Simulation results

To validate and assess the applicability of the developed EAEC-NSGAII technique, experiments were conducted on the IEEE 30-bus system, addressing two bi-objective problems: minimising TFC and EP, minimising TFC and APL, as well as one tri-objective problem involving the optimisation of TFC, EP, and APL. The implementation employed MATLAB 2023a on a PC with a 2.2 GHz i3 core. The EAEC-NSGAII parameters comprised 60 CDs, a maximum of 200 iterations, and an archive set size of 20. The reformulated multiobjective differential evolution (MODE) utilised 60 chromosomes, a maximum of 200 iterations, an archive size of 20, a mutation rate of 0.6, and a crossover rate of 0.9. The IEEE 30-bus system comprises 41 lines, 6 generators, 4 transformers, and 9 shunt reactors. The system functions at a load of 283.4 MW and encompasses 24 variables. Voltage and transformer tap settings range from 0.9 to 1.1 per unit, whereas shunt reactor values are between 0 and 0.05 per unit. Specifications for buses and lines, as well as fuel cost coefficients[12]. Three distinct scenarios were analysed to demonstrate the effectiveness of the EAEC-NSGAII technique.

Case 1: minimization of TFC and EP

The aim is to minimise two conflicting objectives: TFC and EP, which are addressed as a multi-objective optimisation problem framework. Figure 2 presents the optimal set of NDS attained through the EAEC-NSGAII technique, demonstrating its efficacy in exploring NDS within the search space. The BCS is derived from all NDS in the archive set using a fuzzy decision-making approach. Table 1 presents the optimal combination of CVs achieved for BCS using both MODE and EAEC-NSGAII in Case 1, along with the associated TFC, EP, and APL values. The outcomes obtained with alternative algorithms, such as NSGA-II, VEPSO, NEKA, Gaussian bare-bones ICA (GBICA), modified GBICA (MGBICA), and Augmented epsilon constraint NSGAII, are presented in Table 2. The analysis in Table 2 clearly demonstrates that, compared to algorithms in the existing literature, the EAEC-NSGAII method consistently achieves superior performance by producing the most optimal values.

Case 2: minimization of TFC and APL

In this context, we tackle the challenge of minimizing TFC while considering APL as an additional objective, forming a MOOPF problem. Figure 3 illustrates the nondominated solutions obtained using the EAEC-NSGAII method, exposing a diverse collection of Pareto-optimal solutions that are evenly dispersed throughout the search space. Table 1presents the superior set of control variables, along with corresponding TFC, APL, and EP values attained with both Augmented epsilon constraint NSGAII and Enhanced Augmented epsilon constraint NSGAII NSGA-II. These results are compared with various algorithms, including traditional NSGAII.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, No.2, January : 2025

This study addresses the challenge of minimising Total Fuel Consumption (TFC) while incorporating Average Power Loss (APL) as an additional objective, thereby establishing a Multi-Objective Optimal Power Flow (MOOPF) problem. Figure 3 presents the nondominated solutions derived from the EAEC-NSGAII method, revealing a diverse array of Pareto-optimal solutions that are uniformly distributed across the search space. Table 1 presents the optimal set of control variables, along with the corresponding TFC, APL, and EP values obtained using both MODE and EAEC-NSGAII. The results are compared with several algorithms, including NSGA-II, MOHSA, MODE, MOEA/D, and MOABC/D, along with Augmented epsilon constraint NSGAII methods, as outlined in Table 2. This analysis highlights the effectiveness of the EAEC-NSGAII technique in addressing bi-objective problems, illustrating its ability to produce high-quality solutions for various conflicting objectives.

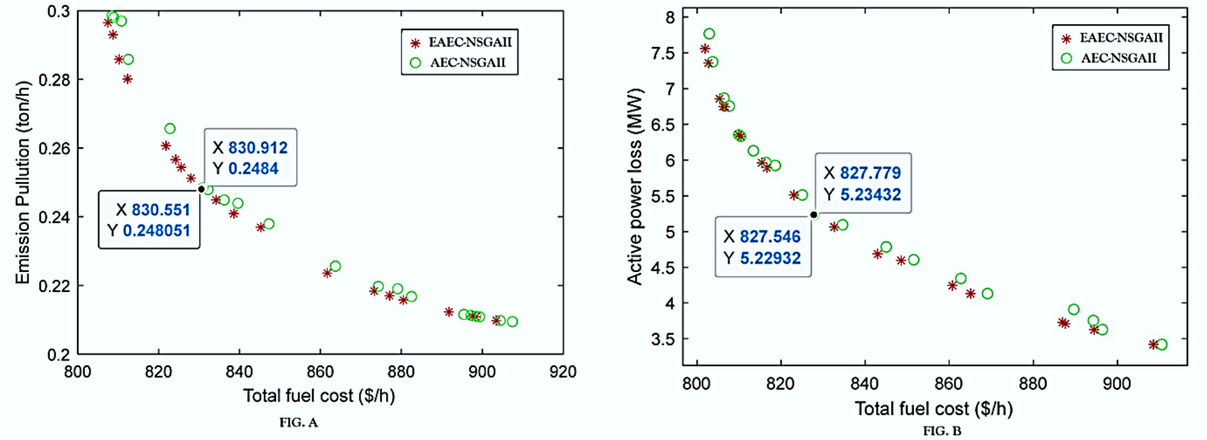

Fig. 5: Pareto front graphical representation attained in simulation for (A) for Case 1 and (B) for Case 2.

Control Variables	AEC-NSGAII Case 1	AEC-NSGAII Case 2	AEC-NSGAII Case 3	EAEC-NSGAII Case 1	EAEC-NSGAII Case 2	EAEC-NSGAII Case 3
P_{g1} (MW)	117.6738	122.79	104.248	117.917	122.92	105.10
P_{g2} (MW)	58.3414	52.121	54.7094	56.6998	52.494	58.886
P_{g5} (MW)	27.1461	30.961	30.9903	25.9895	30.998	31.289
P_{g8} (MW)	35.0000	35.000	35.0000	35.0000	35.000	35.000
P_{g11} (MW)	25.7737	26.430	30.0000	27.3524	26.528	29.382
P_{g13} (MW)	25.0592	21.313	33.1979	25.8268	20.681	28.458
V_{g1} (p.u.)	1.0719	1.1000	1.0970	1.1000	1.0999	1.1000
V_{g2} (p.u.)	1.0593	1.0912	1.0777	1.0871	1.0907	1.0847
V_{g5} (p.u.)	1.0323	1.0685	1.0542	1.0555	1.0687	1.0644
V_{g8} (p.u.)	1.0417	1.0781	1.0703	1.0692	1.0775	1.0832
V_{g11} (p.u.)	1.0788	1.0974	1.0941	1.0999	1.0993	1.0895
V_{g13} (p.u.)	1.0501	1.1000	1.0735	1.1000	1.1000	1.1000
V_{6-9} (p.u.)	1.0334	1.0399	1.0050	0.9583	1.0440	0.9722
V_{6-10} (p.u.)	0.9385	0.9243	1.0048	1.0031	0.9000	1.0446
V_{4-12} (p.u.)	0.9796	1.0010	0.9844	1.0549	0.9784	1.0151
t_{28-27} (p.u.)	0.9753	0.9774	0.9866	0.9765	0.9652	0.9872
b_{sh10} (p.u.)	0.0126	0.0500	0.0150	0.0388	0.0500	0.0381
b_{sh12} (p.u.)	0.0190	0.0436	0.2379	0.0341	0.0498	0.0124
b_{sh15} (p.u.)	0.0393	0.0461	0.2235	0.0500	0.0471	0.0000
b_{sh17} (p.u.)	0.0488	0.0500	0.4190	0.0001	0.0491	0.0246
b_{sh20} (p.u.)	0.0385	0.0463	0.0366	0.0500	0.0385	0.0376
b_{sh21} (p.u.)	0.0500	0.0500	0.0094	0.0306	0.0500	0.0500

b_{sh23} (p.u.)	0.0257	0.0459	0.0423	0.0000	0.0245	0.0376
b_{sh24} (p.u.)	0.0498	0.0497	0.0325	0.0404	0.0500	0.0376
b_{sh29} (p.u.)	0.0247	0.0217	0.0500	0.0359	0.0233	0.0297
TFC ($/h)	**830.9120**	**827.791**	**851.9996**	**830.551**	**827.54**	**847.17**
EP (ton/h)	**0.2486**	0.2603	**0.2300**	**0.2481**	0.2540	**0.2326**
APL (MW)	5.5944	**5.2312**	**4.7459**	5.3860	**5.2293**	**4.7238**

Table 1. Optimal control decision variables of BCS were obtained in all cases.

Case 3: minimization of TFC, EP, and APL

This study addresses a multi-objective optimisation problem involving three complex objectives: Total Fuel Consumption (TFC), Emissions Production (EP), and active Average Path Length (APL). Figure 4 illustrates the nondominated solutions derived from the EAEC-NSGAII technique, highlighting its efficacy in distributing solutions across a broad spectrum. Table 1 presents the optimal set of CVs for this case, along with the corresponding TFC, EP, and APL values achieved using both MODE and EAEC-NSGAII. Table 2 presents a comparison of the optimal values for TFC, EP, APL, and execution time (ET) achieved with EAEC-NSGAII i.e Enhanced Augmented epsilon constraint NSGAII NSGA-II in relation to Augmented epsilon constraint NSGAII NSGA-II. The results clearly demonstrate the superiority of the EAEC-NSGAII i.e. EAEC-NSGAII method compared to EAC-NSGAII. Figure 5 presents the upper and lower limits of load bus voltages attained across all three cases, demonstrating the effectiveness of the EAEC-NSGAII technique in managing voltage constraints. The results demonstrate the effectiveness of the proposed EAEC-NSGAII technique in addressing MOOPF issues, highlighting its ability to produce high-quality solutions and manage conflicting objectives effectively.

Method	**TFC ($/h)**	**EP (ton/h)**	**APL (MW)**	**Execution Time (ET) (s)**
Case 1: minimization of TFC and EP				
MOMICA[17]	865.06	0.22	-	-
PSO-SSO[12]	834.80	0.243	-	-
ESDE[7]	833.47	0.254	-	-
NSGA-II[18]	830.8	0.251	-	-
VEPSO[18]	830.95	0.253	-	-
MOEA/D-SF[17]	829.515	0.250	-	-
NKEA[18]	830.85	0.249	-	-
GBICA[18]	830.85	0.248	-	-
MGBICA[18]	830.85	0.248	-	-
AEC-NSGAII	830.91	0.248	-	54.3
EAEC-NSGAII	830.55	0.248	5.3860	47.2
Case 2: minimization of TFC and APL				
MOAGDE[17]	821.839	-	9.9646	-
MOEA/D-SF[17]	881.01	-	4.144	-
NSGA-II[17]	837.41	-	5.0397	-
MOHS[14]	832.67	-	5.3143	-
DE[9]	828.59	-	5.69	-
MOEA/D[13]	827.71	-	5.2556	-
PSO-SSO[12]	865.1	-	4.093	-
MOABC/D[13]	827.63	-	5.2451	-
AEC-NSGAII	827.79	-	5.23	56.3
EAEC-NSGAII	827.54	0.254	5.2293	48.2
Case 3: minimization of TFC, EP, and APL				
AEC-NSGAII	852.0118	0.2300	4.7502	71.23
EAEC-NSGAII	847.1749	0.2326	4.7238	63.29

Table 2. Comparison of BCS obtained in different cases with other state-of-the-art algorithms.

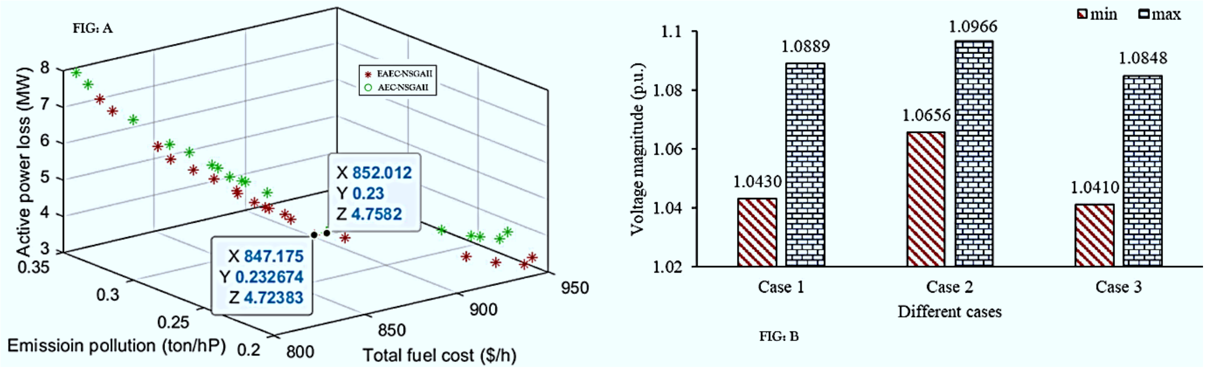

Fig 7. (A)Pareto front graphical representation obtained in simulation Case 3, (B). Figure 5. Minimum and maximum load bus voltages in simulation in all cases.

10. Conclusion

This study effectively implemented the Improved Non-Dominated Sorting Genetic Algorithm II (EAEC-NSGAII) using Enhanced Augmenting Epsilon Constraint handling protocol. It tackles most of challenges associated with Multi-Objective Optimal Power Flow (MOOPF). The proposed method's efficacy was validated using the IEEE 30-bus system across two bi-objective scenarios: minimising Total Fuel Cost (TFC) and Emission Pollution (EP), and optimising TFC and Active Power Loss (APL). Additionally, a tri-objective model was employed, incorporating TFC, EP, and APL. The comparative analysis indicated that EAEC-NSGAII consistently surpassed existing techniques in the literature, providing superior and feasible solutions across all test cases with reference to Augmented epsilon constraint NSGA-II. The EAEC-NSGAII's key features, including the determination of control variable mass via non-dominated rank, normalisation of fitness values across multiple objectives, and the application of crowding distance to preserve solution diversity, were crucial in attaining these outcomes. The incorporation of a fuzzy decision-making mechanism alongside an augmenting epsilon constraint-handling method improved the robustness and adaptability of the optimisation process, facilitating effective constraint management. This study emphasises the simplicity, computational efficiency, and capacity of EAEC-NSGAII to preserve population diversity, positioning it as a valuable tool for complex multi-objective optimisation challenges in power systems. The demonstrated success in resolving MOOPF issues highlights its potential for wider applications, such as tackling the Combined Heat and Power Economic Dispatch, Complex voltage stability problem with the integration of renewable energy. This expansion would demonstrate EAEC-NSGAII’s adaptability and significance in promoting sustainable energy management. Future research will concentrate on investigating various parameter configurations for EAEC-NSGAII, evaluating its efficacy on a range of real-world multi-objective challenges, and broadening its application to domains such as renewable energy optimisation and system planning. The EAEC-NSGAII framework represents a notable advancement in multi-objective optimisation methods, facilitating progress in the operation and control of power systems.

11. References

[1]. Dommel, H. W., & Tinney, W. F. (1968). Optimal power flow solutions. *IEEE Transactions on Power Apparatus and Systems, 87*, 1866–1876.
[2]. Scott, B., & Hobson, E. (1978). Power system security control calculations using linear programming- part I. *IEEE Transactions on Power Apparatus and Systems, 97*(5), 1713–1720.
[3]. Sun, D. I., Ashley, B., Brewer, B., & Tinney, W. F. (1984). Optimal power flow by Newton approach. *IEEE Transactions on Power Apparatus and Systems*, *103*(10), 2864–2880.
[4]. Omar, A. A., AL-Smadi, M., Shaher, M., & Tasawar, H. (2016). Numerical solutions of fuzzy differential equations using reproducing kernel Hilbert space method. *Soft Computing, 20*(8), 3283–3302.

[5]. Omar, A. A., AL-Smadi, M., Shaher, M., & Tasawar, H. (2017). Application of reproducing kernel algorithm for solving second-order, two-point fuzzy boundary value problems. *Soft Computing, 21*(13), 7191–7206.

[6]. Wang, Y., Wang, H., et al. (2024). Multi-objective coordinated EV charging strategy in distribution networks using an improved augmented epsilon-constrained method. *Applied Energy, 369*, 123547. https://doi.org/10.1016/j.apenergy.2024.123547

[7]. Omar, A. A. (2017). Adaptation of reproducing kernel algorithm for solving fuzzy Fredholm-Volterra integrodifferential equations. *Neural Computing and Applications, 28*(7), 1591–1610.

[8]. Pulluri, H., Sharma, R. N., & Sharma, V. (2017). An enhanced self-adaptive differential evolution-based solution methodology for multi-objective optimal power flow. *Applied Soft Computing, 54*, 229–245.

[9]. Surender Reddy, S., & Bijwe, P. R. (2019). Differential evolution-based efficient multi-objective optimal power flow. *Neural Computing and Applications, 31*, 509–522.

[10]. Abido, M. A., & Al-Ali. (2012). Multi-objective optimal power flow using differential evolution. *Arabian Journal for Science and Engineering, 37*, 991–1005.

[11]. Suman, S., Akbel, M., & Kahraman, H. T. (2021). Development of the multi-objective adaptive guided differential evolution and optimization of the MO-ACOPF for wind/PV/tidal energy sources. *Applied Soft Computing, 112*, 107814.

[12]. Deb, K., Agarwal, S., Pratap, A., & Meyarivan, T. (2002). A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation, 6*(2), 182–197.

[13]. Ragab, A. E., Selim, F., Bachir, B., & Abido, M. A. (2020). A novel multi-objective hybrid particle swarm and salp optimization algorithm for technical-economical environmental operation in power systems. *Energy, 193*, 116817.

[14]. Iman, M., Daryani, A., & Karami, M. (2013). Artificial bee colony algorithm for solving multi-objective optimal power flow problem. *International Journal of Electrical Power & Energy Systems, 53*, 219–230.

[15]. Omar, A. A., Al-Smaidi, M., Shaher, M., & Tasawar, H. (2016). Numerical solutions of fuzzy differential equations using reproducing kernel Hilbert space method. *Soft Computing, 20*(8), 3283–3302.

[16]. Omar, A. A., Al-Smaidi, M., Shaher, M., & Tasawar, H. (2017). Application of reproducing kernel algorithm for solving second-order, two-point fuzzy boundary value problems. *Soft Computing, 21*(13), 7191–7206.

[17]. Omar, A. A. (2017). Adaptation of reproducing kernel algorithm for solving fuzzy Fredholm-Volterra integro-differential equations. *Neural Computing and Applications, 28*(7), 1591–1610.

[18]. Bhandari, R. N., & Sharma, V. (2017). An enhanced self-adaptive differential evolution-based solution methodology for multi-objective optimal power flow. *Applied Soft Computing, 54*, 229–245.

[19]. Surender Reddy, S., & Bijwe, P. R. (2019). Differential evolution-based efficient multi-objective optimal power flow. *Neural Computing and Applications, 31*, 509–522.

[20]. Abido, M. A., et al. (2012). Multi-objective optimal power flow using differential evolution. *Arabian Journal for Science and Engineering, 37*, 991–1005.

[21]. Iman, S., Abbe, M., & Kahraman, H. T. (2021). Development of the multi-objective adaptive guided differential evolution and application of the MO-ACOPF for wind/PV/dial energy sources. *Applied Soft Computing, 112*, 107814.

[22]. Deb, K., Agarwal, S., Pratap, A., & Meyarivan, T. (2002). A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation, 6*(2), 182–197.

[23]. Ragab, A. E., Selim, H., Bachir, B., & Bido, M. A. (2020). A novel multi-objective hybrid particle swarm and salp optimization algorithm for technical-economical environmental operation in power systems. *Energy, 193*, 116817.

[24]. Rezaei, M., Daryani, A., & Karami, M. (2013). Artificial bee colony algorithm for solving multi-objective optimal power flow problem. *International Journal of Electrical Power & Energy Systems, 53*, 219–230.
[25]. Sivasubramani, S., & Swarup, K. S. (2011). Multi-objective harmony search algorithm for optimal power flow problem. *International Journal of Electrical Power & Energy Systems, 33*, 745–752.
[26]. Arindabad, B., & Proves, K. N. (2012). Solution of multi-objective optimal power flow using gravitational search algorithm. *IET Generation, Transmission & Distribution, 6*(8), 751–763.
[27]. Apu, B., & Proves, K. N. (2015). Solution of optimal power flow using non-dominated sorting multi-objective opposition-based gravitational search algorithm. *International Journal of Electrical Power & Energy Systems, 64*, 1237–1250.
[28]. Li, H., et al. (2023). Multi-objective pathfinder algorithm for multi-objective optimal power flow problem with random renewable energy sources: wind, photovoltaic and tidal. *Scientific Reports, 13*, 10647.
[29]. Shaemi, M., Ghavidel, S., Ghanbarian, M. M., & Gitizadeh, M. (2015). Multi-objective optimal electric power planning in the power system using Gaussian bare-bones imperialist competitive algorithm. *Information Sciences, 294*, 286–304.
[30]. Chen, M. R., Yang, L. Q., & Zeng, G. Q. (2023). IFA-FO: An improved firefly algorithm hybridized with external optimization for continuous constrained optimization problems. *Applied Soft Computing, 66*, 2943–2964.
[31]. Li, H., Wang, Z., Ngo, P., & Li, Y. (2024). Promoting objective knowledge transfer: a cascaded fuzzy system for solving dynamic optimization problems. *IEEE Transactions on Fuzzy Systems*. https://doi.org/10.1109/TFUZZ.2024.3443207
[32]. Li, H., Wang, Z., Ngo, P., & Zeng, N. (2022). A novel dynamic multi-objective optimization algorithm with non-inductive transfer learning based on multi-strategy adaptation. *IEEE Transactions on Neural Networks and Learning Systems, 35*. https://doi.org/10.1109/TNNLS.2022.3329561
[33]. Naderi, E., Mirzaei, S., Trimble, J. P., & Cantrell, D. A. (2023). Multi-objective optimal power flow incorporating flexible alternating current transmission systems: application of a wavelet-selected evolutionary algorithm. *Electrical Power Components and Systems, 52*(5), 766–795.
[34]. Li, H., Wang, Z., & Ngo, P. (2024). A new dynamic multi-objective optimization algorithm with hierarchical response system. *IEEE Transactions on Computational Science and Systems, 11*(2), 2494–2512.
[35]. Puluri, H., Ramesh, R., & Sharma, V. (2016). A solution network based on stud krill herd algorithm for optimal power flow problems. *Soft Computing, 22*(1), 159–176.