International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

IJSRA

(RESEARCH ARTICLE)

Multi-objective driving training-based optimization algorithm for optimizing power losses and voltage profile in power systems

Edmond Randriamora *, Olivier Mickaël Ranarison and Rivo Mahandrisoa Randriamaroson

Doctoral School of Science and Engineering Techniques and Innovation, University of Antananarivo, Madagascar.

International Journal of Science and Research Archive, 2026, 19(03), 923-931

Publication history: Received on 06 May 2026; revised on 22 June 2026; accepted on 24 June 2026

Article DOI: https://doi.org/10.30574/ijsra.2026.19.3.1385

Abstract

Managing active power losses and maintaining an acceptable voltage profile are two conflicting yet critical objectives in modern power system operations. This paper presents a novel Multi-Objective Driving Training Based Optimization (MODTBO) algorithm to solve the multi-objective optimal power flow problem. Unlike the original mono-objective DTBO algorithm which operates on three separates phases, the proposed multi-objective variant streamlines the search process into two main phases: instructor training, and combined patterning and personal practice. To effectively handle the multi-objective space, MODTBO integrates non-dominated sorting and crowding distance mechanisms to rank the population and adaptively select driving instructors. The performance of the MODTBO algorithm is evaluated on standard IEEE 30-bus system by simultaneously minimizing total active power transmission losses and bus voltage deviations while satisfying strict equality and inequality constraints. Furthermore, a Fuzzy Logic-based approach is employed to extract the best compromise solution from the generated Pareto-optimal front, aiding operators in decision-making. Simulation results demonstrate that MODTBO provides a well-distributed Pareto front with high intensification and diversification. It outperforms the single-objective Modified Driving Training Based Optimization (MDTBO) frameworks, specifically those focusing individually on either voltage profile enhancement or active loss minimization, by successfully compromising both conflicting goals in a single optimization run with superior convergence. Consequently, the proposed algorithm offers an efficient and practical tool for power system operators to balance system efficiency and voltage stability.

Keywords: Voltage profile; Active power losses; Optimal power flow; Multi-Objective; Driving Training Based Optimization; Pareto front

1. Introduction

The sustainable and secure operation of modern electrical power grids requires a continuous balance between operational efficiency and voltage stability. In power system engineering, the optimal power flow (OPF) problem stands as a fundamental tool for system operators to adjust control variables (generator voltages, transformer tap changers, and reactive power compensators) while satisfying a complex set of equality and inequality constraints. Traditionally, OPF formulations focused primarily on economic dispatch or single-objective minimization of active power losses. However, the integration of highly volatile renewable energy sources and the constant increase in load demand have significantly pressured transmission grids, leading to undesirable voltage fluctuations and increased thermal stresses. Consequently, minimizing active power transmission losses and reducing bus voltage deviations have emerged as two conflicting yet critically vital objectives for ensuring both grid efficiency and system security.

Optimizing power systems under these conditions leads to a highly non-linear, non-convex, and multi-objective optimization challenge. When active power losses are minimized, voltage profiles may degrade, and conversely, boosting voltage stability often requires reactive power re-allocation that can increase system losses. Classical

* Corresponding author: Edmond Randriamora

deterministic optimization techniques, such as linear programming and interior-point methods often struggle with such complex surface, as they are highly sensitive to initial conditions and prone to getting trapped in local optima. To circumvent these limitations, metaheuristic optimization algorithms have gained widespread adoption due to their gradient-free nature, flexibility, and robust global search capabilities.

Over the past few decades, various nature-inspired and human-inspired metaheuristics have been successfully adapted to multi-objective power system problems. In the literature, M. A. Abido (2008) proposed Multi-Objective Particle Swarm Optimization (MOPSO) algorithm to optimize cost and voltage stability simultaneously [1]. In 2022, T. H. B. Huy and al. used Multi-Objective Search Group Algorithm (MOSGA) to concurrently optimize the fuel cost, emissions, and active power loss, tested on IEEE 30-bus and 57-bus systems [2]. In 2024, H. Pulluri and al. introduced Nondominated Sorting Colliding Bodies Optimization (NSCBO) technique to solve both bi- and tri-objective models (fuel cost, emission profile, active power loss) of OPF on IEEE 30-bus [3].

Recently, in 2022, M. Dehghani and al. introduced the Driving-Training Based Optimization (DTBO) algorithm for single-objective problems, mimicking the human process of acquiring driving skills through instructor training, patterning, and personal practice [4]. This method has been modified (MDTBO) by O. M. Ranarison and al. to solve single-objective OPF problem. With MDTBO, in case where objective is voltage profile improvement, active power loss and voltage deviation obtained are respectively 9.8513 MW and 0.1322. In case where objective is minimizing active power loss, results are 2.9162MW and 1.6784 [5]. Although the single-objective MDTBO algorithm has demonstrated excellent performance for OPF, its use forces operators to perform independent optimizations, either for loss minimization or voltage correction. This single-criterion focus fails to capture the trade-offs required in real-time power system operations, yielding solutions that optimize one parameter while severely compromising the other. To bride this gap, this paper introduces a Multi-Objective Driving Training Based Optimization (MODTBO) algorithm to solve the multi-objective OPF problem. MODTBO was firstly proposed in 2024 by W. Aouadj and al. and tested on ZDT3 and DTLZ8 benchmarks [6]. Unlike its mono-objective predecessor, which relies on a three-phase structure, the proposed MODTBO streamlines the optimization process into two main phases: instructor training, and a combined patterning and personal practice phase. The algorithm integrates non-dominated sorting and crowding distance mechanisms to effectively handle and maintain a diverse Pareto-optimal front. Furthermore, because a Pareto front offers a wide set of trade-off solutions, a Fuzzy Logic-based decision-making approach is implemented to systematically extract the single best compromise solution, mimicking an expert operator’s preference. The effectiveness of the proposed approach is validated on standard IEEE 30-bus system.

2. Materials and methods

2.1. IEEE 30-bus system

In this study, bus data and line data for IEEE 30-bus system in [5] are used. The control variables of the system are: active powers and voltage magnitudes for the slack bus (PG1 and VG1), bus 2 (PG2 and VG2), bus 5 (PG3 and VG3), bus 8 (PG4 and VG4), bus 11 (PG5 and VG5), bus 13 (PG6 and VG6), tap transformers settings on line 11 (T1), line 12 (T2), line 15 (T3) and line 36 (T4), and shunt VAR compensators on bus 10 (QC1), bus 12 (QC2), bus 15 (QC3), bus 17 (QC4), bus 20 (QC5), bus 21 (QC6), bus 23 (QC7), bus 24 (QC8) and bus 29 (QC9).

2.2. Objective function

The main objective of solving a multi-objective problem is to optimize several independent objective functions simultaneously. A multi-objective function can be defined as follows:

$$Min\, F(x,u) = [F_1(x,u), F_2(x,u), \dots, F_m(x,u)] \quad (1)$$

In this study, two objectives are considered: voltage profile improvement (or minimization of Voltage Deviation index) and minimization of active power losses through transmission line. The multi-objective function is solved using the Pareto optimization method or weighting factors as follows:

$$F(x,u) = \omega_1 \left(\sum_{i=1}^{NPQ} |(V_i - 1)| \right) + \omega_2 \left(\sum_{i=1}^{NTL} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j cos\delta_{ij}) \right) \quad (2)$$

Where ω_1 and ω_2 are the weighting factors selected based on the relative importance of one objective compared to the others.

2.3. MODTBO

The proposed MODTBO algorithm involves two phases: instructor training and patterning and personal practice. It uses non-dominated sorting and crowding distance mechanisms to sort individuals and select driving instructors [6].

Here is the MODTBO algorithm:

2.3.1. Step1: Initialization

- Initialize a population P of N learner drivers randomly within the lower (L) and upper (U) bounds.
- Evaluate the multi-objective fitness functions for each individual.
- Apply non-dominated sorting and crowding distance to sort the population.
- Identify and create a list of Driving Instructors (DI) from the best-performing solutions.
- Set the current function evaluation count (FE=0) and maximum evaluations (MaxFE).

2.3.2. Step 2: Main Loop (While FE<MaxFE)

- *Phase 1: Instructor Training*

For each learner driver X_i in population P:

Randomly select a driving instructor DI_k from the instructor list.

Generate two random numbers, R and I.

Update the decision vector to generate a temporary candidate X_i^{P1}:

$$X_i^{P1} = X_i + R \cdot (DI_k - I \cdot X_i) \tag{3}$$

Evaluate the objectives of X_i^{P1} and increment FE.

Selection: Merge P and P1 ($P_{merged} = P \cup P1$). Sort using non-dominated sorting and crowding distance, then select he N best individuals to form the new population P for Phase 2.

- *Phase 2: Patterning and Personal Practice*

Update the patterning index using:

$$PI = 0.01 + 0.9 \cdot \left(1 - \frac{FE}{MaxFE}\right) \tag{4}$$

For each learner driver X_i in the updated population P:

If rand<0.5 (Instructor Skill Patterning):

Select a random instructor DI_k and generate candidate X_i^{P2}:

$$X_i^{P2} = \begin{cases} X_i + PI \cdot X_i - (1 - PI) \cdot DI_k & if\ rand < 0.5 \\ X_i + (1 - PI) \cdot X_i - PI \cdot DI_k & otherwise \end{cases} \tag{5}$$

Else (Personal Practice):

Keep the vector the same but modify one randomly selected decision variable index j:

$$X_{i,j}^{P2} = X_{i,j} + (1 - 2rand) \cdot PI \cdot \left(U_j - L_j\right) \tag{6}$$

Evaluate the objectives of X_i^{P2} and increment FE.

Selection: Merge P and P2 ($P_{merged} = P \cup P2$). Sort by rank and crowding distance, the retain the top N individuals for the next generation.

2.3.3. Step 3: Termination

Output the Pareto-optimal Set (PS) and its corresponding Pareto-optimal Front (PF) from the final non-dominated population.

2.4. Fuzzy Logic-Based Best Compromise Selection Algorithm

Here is the complete algorithm for selecting the best compromise solution from a Pareto front using Fuzzy Logic:

2.4.1. Step 1: Identify Objective Bounds

For each objective function m (where m=1,2, …, M), find the minimum and maximum values among all non-dominated solutions in the final Pareto front: f_m^{min} the best possible value found and f_m^{max} the worst possible value found.

2.4.2. Step 2: Calculate Fuzzy Membership Value $\boldsymbol{\mu_m^i}$

For each solution i (where i=1,2, …, N) and each objective m, compute its fuzzy satisfaction membership degree. A value of 1 represents perfect satisfaction, while 0 represents no satisfaction. For minimization objectives:

$$\mu_m^i = \begin{cases} 1 & if\ f_m^i \le f_m^{min} \\ \dfrac{f_m^{max} - f_m^i}{f_m^{max} - f_m^{min}} & if\ f_m^{min} < f_m^i < f_m^{max} \\ 0 & if\ f_m^i \ge f_m^{max} \end{cases} \tag{7}$$

2.4.3. Step 3: Calculate Global Achievement Cardinal $\boldsymbol{\mu^i}$

Compute the normalized global performance score for each solution I relative to the entire population.

$$\mu^i = \frac{\sum_{m=1}^{M} \omega_m \cdot \mu_m^i}{\sum_{i=1}^{N} \sum_{m=1}^{M} \omega_m \cdot \mu_m^i} \tag{8}$$

ω_m represents the relative importance weight assigned to objective m. If all objectives are equally important, set $\omega_m = 1/M$ for all objectives.

2.4.4. Step 4: Extract Best Compromise Solution

The optimal trade-off solution is selected by maximizing the overall global fuzzy membership value:

$$Best\ Solution = \arg\max(\mu^i)\ , i = 1 \dots N \tag{9}$$

3. Results and discussion

3.1. Pareto-optimal fronts

The figure 1 shows the Pareto-optimal fronts for a multi-objective optimal power flow problem solved over three separates runs using MODTBO with 500 iterations.

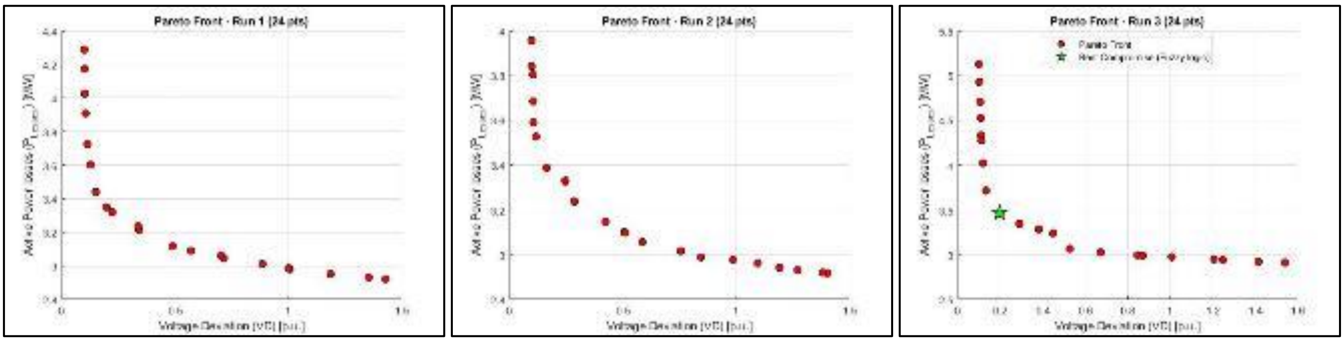

Figure 1 Pareto-optimal fronts over three separate runs using MODTBO

3.1.1. Analysis of the Trade-off Curve

- Conflicting Objectives: A clear, inversely proportional relationship exists between power losses and voltage deviation.
- Extreme zones: Minimizing voltage deviation (0.1 p.u) drives power losses to their maximum peak (4.0-5.1 MW).
- Loss Minimization: Reducing losses below 3.0 MW forces voltage deviation to degrade significantly up to 1.4-1.5 p.u.
- Convex shape: the well-distributed, smooth convex curve indicates that the problem is well-formulated and bounded.

3.1.2. Algorithm performance and stability:

- Consistent Yield: the algorithm consistently discovers exactly 24 non-dominated solutions in each run.
- High Repeatability: Run 1 and Run 2 yield nearly identical front shapes, proving strong algorithmic stability.
- Exploratory Capability: Run 3 expands slightly further into the extreme boundaries, capturing a higher loss peak (>5.1 MW).
- Convergence: 500 iterations prove highly sufficient to achieve a fully matured and well-spread Pareto front.

3.1.3. Best compromise decision (Run 3):

- Knee-point selection: the fuzzy logic mechanism successfully identifies the knee point of the curve (VD = 0.1967 p.u, Plosses = 3.4646 MW).
- Optimal balance: this green star represents the sharpest geometric trade-off available to system operators.
- High efficiency: it achieves a major 32% reduction in losses (from 5.1 to 3.4646 MW) while sacrificing only 0.1 p.u of voltage deviation.
- Diminishing returns: moving past this star to the right yields negligible loss savings at the expense of massive voltage degradation.

3.2. Evolution of the Pareto representative, cost and penalty over iterations

The figure 2 tracks the step-by-step convergence history of the representative best compromise solution, costs and system penalties over 500 iterations.

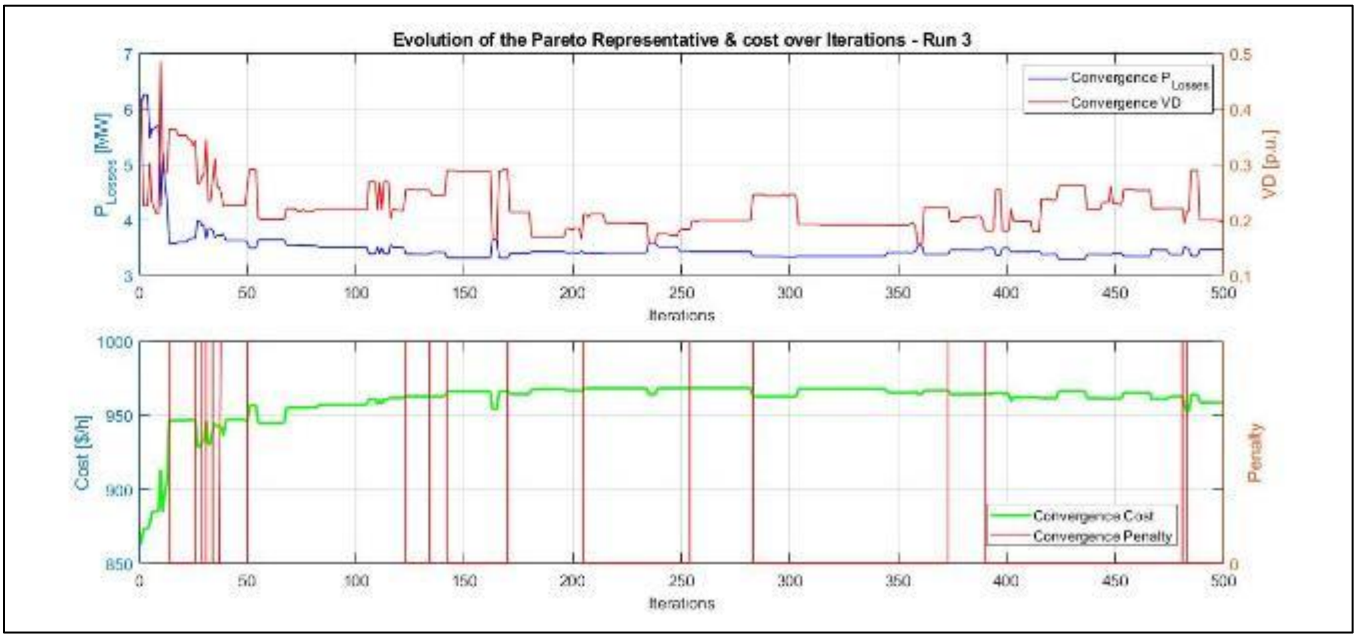

Figure 2 Convergence history of the representative best compromise solution, costs and system penalties over 500 iterations – run 3

3.2.1. Multi-objective convergence history (top plot):

Exploration phase (0-50 iterations): high volatility occurs as the algorithm widely explores the search space. Active power losses spike up to 6.3 MW, while voltage deviation hits peaks near 0.5 p.u.

Exploitation phase (50-500 iterations): the blue curve (Plosses) stabilizes smoothly around 3.47 MW, matching the green star selected in the Pareto front.

Dynamic trade-offs: the red curve (VD) exhibits step-like fluctuations between 0.18 and 0.30 p.u as the front refines, ultimately securing its optimal balance around 0.20 p.u.

3.2.2. Economic cost and penalty tracking (bottom plot):

Cost evolution: economic operating cost (green curve) starts low (about 860 $/h) but rapidly shifts upward to stabilize between 950 and 970 $/h. This confirms that the cheaper initial states were structurally unfeasible.

Penalty frequency: red vertical lines flag active system constraint violations.

Constraint handling: penalties are highly dense before iteration 50. Post-iteration 50, violations drop drastically into isolated, brief spikes (e.g., iterations 130, 255, 480).

Self-correction: the rapid disappearance of these red lines proves MODTBO's capability to quickly push solutions back into the valid, secure operating envelope.

3.3. Control variables configuration

The figure 3 represents the control variables configuration after 500 iterations for the run 3.

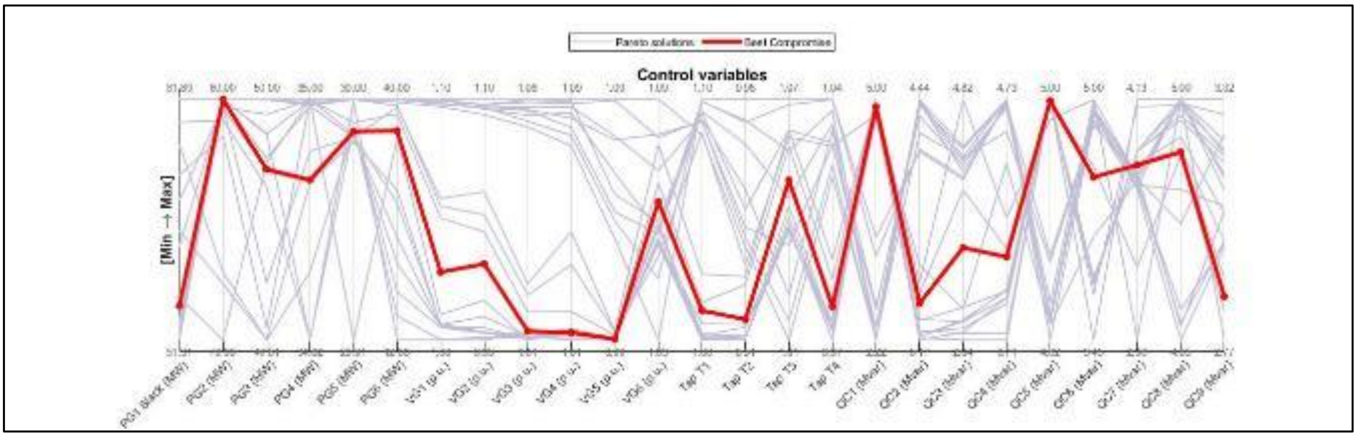

Figure 3 Control variables configuration after 500 iterations – run 3

This parallel coordinates plot displays the full set of optimization decision variables for all 24 Pareto solutions (grey lines) and highlights the fuzzy-selected best compromise (solid red line).

Active power generation: PG2, PG5 and PG6 are driven directly to their upper operating limits (80 MW, 30 MW and 40 MW). This distribution strategy shifts generation to more efficient or cost-effective units to minimize network losses.

Generator voltages: voltage profiles are tightly managed. VG3, VG4 and VG5 are kept near their lower bounds (about 1.01 p.u), whereas VG6 is elevated to drive necessary reactive power adjustments.

Transformer taps: taps are varied dynamically across their ranges to regulated local voltage steps. T3 is tuned higher (about 1.01), while T1, T2, and T4 are pushed lower to control power flow.

Shunt capacitors: reactive compensation units QC1, QC5 and QC8 operate at their absolute maximum capacity (5 Mvar). This maximum local VAR support is vital for stabilizing the grid voltage profile near heavy load centers.

3.4. Global objectives and performance indicators

The figure 4 maps out the ultimate performance trade-offs across the Pareto set (green lines) against the Best compromise (thick blue line).

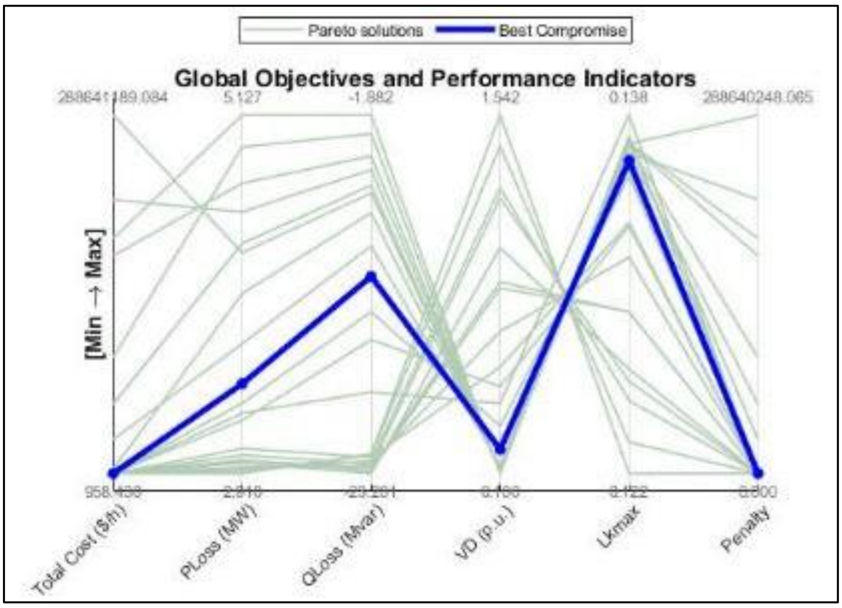

Figure 4 Global objectives and performance indicators after 500 iterations – run 3

Total cost: the blue line hits the absolute lower boundary of the feasible envelope (958.43$/h), ensuring highly economical operation.

Active power loss: placed in a well-balanced mid-to-low position (3.4646 MW) within the full available spectrum (2.91 to 5.127 MW).

Voltage deviation: successfully contained near the absolute minimum floor (0.1967 p.u), preventing broad grid voltage degradation.

Stability index (Lkmax): the best compromise exhibits a higher index peak (~0.138). However, since the maximum axis limit is very low, transmission lines remain completely safe from thermal overload.

System Penalty: crucially, the blue line drops to exactly 0.0. This confirms that the fuzzy logic selection mechanism rejects penalized boundaries and ensures a perfectly legal, secure system state.

3.5. Active power losses profile

The plot in figure 5 illustrates the distribution of active power losses across all 41 transmission lines of the network.

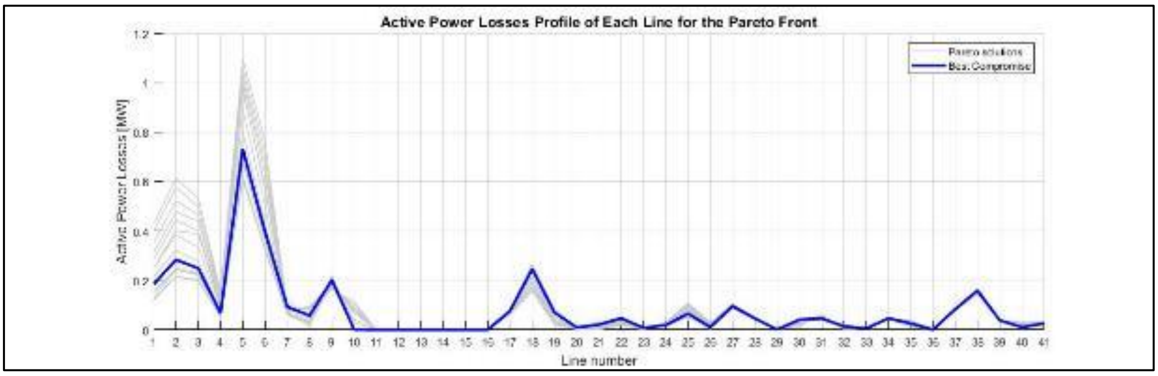

Figure 5 Active power losses profile of each line for the Pareto Front – run 3

Highly localized loss distribution: most of the transmission lines (specifically lines 11-16 and 20-41) maintain near-zero losses across all Pareto solutions.

Critical bottleneck: line 5 is the most heavily stressed corridor in the grid. In some Pareto solutions, its loss spikes up to 1.1 MW.

Peak mitigation: the fuzzy best compromise (solid blue line) successfully suppresses this massive bottleneck peak down to roughly 0.72 MW.

Secondary stress points: lines 1, 2, 3 and 18 also experience elevated thermal stress. The best compromise enforces strict active power routing to keep these moderate losses balanced (e.g., clamping line 18 at 0.25 MW).

3.6. Voltage profile

The figure 6 evaluates the voltage quality across all 30 buses of the electrical network, comparing the solutions against standard regulatory limits (0.95 to 1.05 p.u).

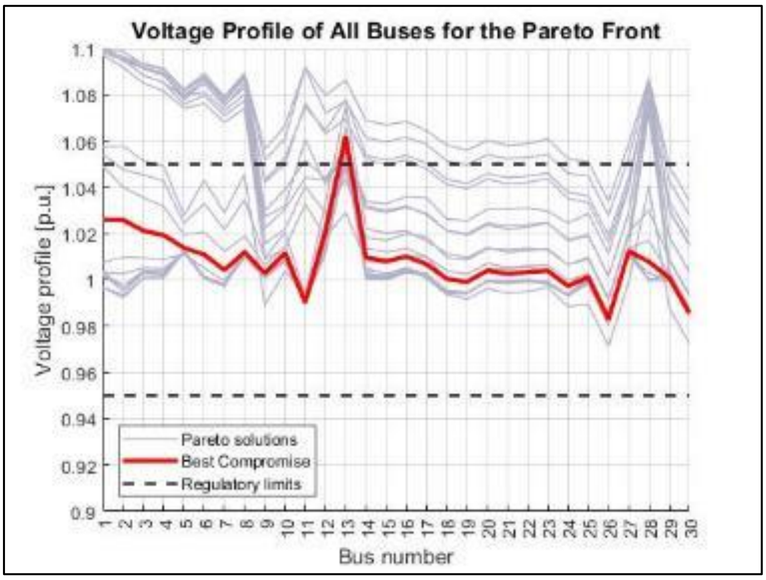

Figure 6 Voltage profile of all buses for the Pareto Front – run 3

Extreme solutions (Grey lines): many Pareto solutions, specifically those prioritizing absolute minimum power losses, completely compromise grid security. They cause severe over voltages up to 1.10 p.u at buses 1-4, 8, 12 and 27-28.

Voltage smoothing: the best compromise (solid red line) demonstrates excellent power quality control. It forces the majority of the grid's buses to sit tightly around the ideal 1.0 p.u. nominal baseline.

Constraint compliance: by bringing the entire profile down, the best compromise avoids the major over voltages of the extreme solutions. Only bus 13 exhibits a minor, acceptable peak at 1.06 p.u. to support local reactive power flow.

Safe lower margins: no solution drops close to the lower critical safety boundary of 0.95 p.u., indicating excellent voltage stability against voltage collapse.

4. Conclusion

The proposed Multi-Objective Driving Training Based Optimization (MODTBO) algorithm, enhanced by a Fuzzy Logic decision-making approach, efficiently solves the multi-objective optimal power flow problem on the IEEE 30-bus system by balancing active power loss minimization and voltage deviation reduction. The approach addresses conflicts inherent in single-objective methods by producing a well-distributed Pareto front, offering a robust, secure decision-support tool for grid operators.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] M. A. Abido, “Multiobjective particle swarm optimization for optimal power flow problem”, in 12th International Middle-East Power System Conference, IEEE, 2008, DOI: 10.1109/MEPCON.2008.4562380.

[2] T. H. B. Huy, D. Kim and D. N. Vo, “Multiobjective Optimal Power Flow Using Multiobjective Search Group Algorithm”, in IEEE Access, vol. 10, pp. 77837-77856, 2022, DOI: 10.1109/ACCESS.2022.3193371.

[3] H. Pulluri, K. Rao, C. Sriram, et al, “Multiobjective optimal power flow solutions using nondominated sorting colliding bodies optimization”, Sci Rep 14, 26593, 2024, DOI: 10.1038/s41598-024-77275-z.

[4] Mohammad Dehghani, Eva Trojovska, Pavel Trojovsky, “A new human-based metaheuristic algorithm for solving optimization problems on the base of simulation of driving training process”, Scientific reports, 2022, DOI: 10.1038/s41598-022-14225-7.

[5] O. M. Ranarison, E. Randriamora, H. Andriatsihoarana, , “Optimal Power Flow Using Modified Driving-Training Based Optimization algorithm”, International Journal of Advances in Engineering and Management, vol. 7, Issue 02 Feb. 2025, pp. 846-860, DOI: 10.35629/5252-0702846860.

[6] W. Aouadj, R. Seghir, “A New Multi-Objective Driving-Training-Based Optimization Algorithm”, AIJR Abstracts, Feb. 2024, pp. 36-38, DOI: 10.21467/abstracts.163.