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Economic and Green Dispatch in Multi-Area Power Systems: An Approach of using NDSGA-II

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***Abstract*— This paper introduces an improved strategy for multi- area economic and environmental dispatch (MAEED) utilizing the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). As the global push for sustainable energy solutions intensifies, optimizing power distribution to minimize both cost and emissions has become essential. This work formulates MAEED as a bi-goal nonlinear constrained optimization problem incorporating power balance, generation capacity, and tie-line limits. The proposed NSGA-II is benchmarked against Strength Pareto Evolutionary Algorithm II (SPEA-II) and other contemporary methods. Simulation results on a four-area power system illustrate that NSGA-II consistently outperforms alternatives by offering superior trade-offs between cost and emissions. Recent studies support these findings, highlighting the robustness of evolutionary approaches in multi-goal dispatch problems.**

I. INTRODUCTION

Power generation from fossil fuels continues to be a major contributor to air pollution, releasing harmful gases like sulfur oxides, carbon oxides, and nitrogen oxides into the atmosphere. These pollutants not only pose serious risks to human health and other living organisms but also contribute to vegetation damage, acid rain, reduced visibility, and global warming.

Growing environmental awareness, along with regulatory frameworks like the Clean Air Act Amendments of 1990, have pushed power stations to actively work towards reducing emissions. However, this creates a challenging trade-off: producing electricity at the lowest cost while also minimizing environmental impact.

More than a few methods have been projected to reduce emissions—such as installing post-combustion cleaning systems, using cleaner fuels, replacing older fuel burners, and optimizing how power is dispatched. Among these, power dispatch optimization within emission limits is often seen as the most practical and cost-effective strategy, especially since the other approaches usually require substantial capital investment and infrastructure changes.

The dual goals of minimizing both fuel cost and emissions often conflict, and must be addressed together to find a balanced, feasible solution. Initially, classical optimization techniques like linear programming were employed, but they struggled with the complexity of real-world systems[1-17]. As a result, more sophisticated methods—like evolutionary and swarm-based algorithms—have gained popularity. These modern techniques are better equipped to navigate the complicated landscape of multi-objective optimization problems [18-25].

Over the years, many such methods have been developed and tested for Economic Emission Dispatch (EED) in single-area systems, taking into account real-world constraints [27]. More recently, Multi-Objective Evolutionary Algorithms (MOEVAs) have emerged, providing effective solutions via Pareto-optimal fronts obtained in a single execution, using techniques such as the Strength Pareto Evolutionary Algorithm II (SPEA II), Non-Dominated Sorting Genetic Algorithm (NSGA), its improved version NSGA-II, Multi-Objective Particle Swarm Optimization (MOPSO), and others have shown promising results in this space [26-30].

However, modern power systems are rarely isolated. They are usually part of interconnected multi-area networks, where power generation and distribution happen across different regions linked via tie-lines. This adds another layer of complexity. While earlier research mostly focused on profitable dispatch in these multi-area systems, recent attention has turned to Multi-Area Economic Environmental Dispatch Strategies (MAEEDS), which consider both cost and environmental factors [31-48].

In MAEEDS, the goal is to determine how much power should be generated in each area, and how much should be exchanged across regions, so that both total cost and emissions are minimized—while still respecting operational constraints like generation capacity, tie-line limits, and demand-supply balance[45-55].

Solving such complex, constraint-heavy optimization problems is no easy task. There's no one-size-fits-all key solution, and choosing the right optimization technique is critical.

In this context, the present work focuses on applying NSGA-II to solve the MAEEDS problem, modeled as a nonlinear, constrained, multi-objective optimization challenge.

A four-area test system has been used to validate this approach. For comparison, the same system is also analyzed using SPEA II. Benchmark results from other methods—such as multi-objective particle swarm optimization(PSO), differential evolution(DE), and the Jaya algorithm—are taken from the literature.

Results from the study show that NSGA-II provides superior performance in subsequent monetary and ecological goals, making it a strong candidate for real-world MAEEDS applications.

II. PROBLEM FORMULATION

This MAEED is formulated here as in convention. The set of governing equations and constraints are summed up below

Objectives

Cost

$$f_1=\sum_{g=1}^{NA}\sum_{h=1}^{NC_g} f_{1gh}\left(p_{gh}\right) \tag{1}$$

$$f_{1gh}\left(p_{gh}\right)=a_{gh}+b_{gh}p_{gh}+c_{gh}p_{gh}^2 + d_{gh}\times\sin\left\{e_{gh}\times(p^{\min}-p_{gh})\right\} \tag{2}$$

Emission

$$f_{1'}=\sum_{g=1}^{NA}\sum_{h=1}^{NC_g} f_{1'gh}\left(p_{gh}\right) \tag{3}$$

$$f_{1'gh}\left(p_{gh}\right)=\alpha_{gh}+\beta_{gh}p_{gh}+\gamma_{gh}p^2+\eta_{gh}\exp\left(\delta_{gh}p_{gh}\right) \tag{4}$$

Constraints

Production-demand balance

$$\sum_{h=1}^{NC_g} p_{gh}=p_{Dg}+p_{Lg}+\sum_{o,o\neq 1} T_{go} \qquad \forall g\in NA \tag{5}$$

Tie line capacity

$$-T_{go}^{max}\leq T_{go}\leq T_{go}^{max} \tag{6}$$

Power production capacity

$$-P_{go}^{min}\leq P_{go}\leq P_{go}^{max} \qquad \forall g\in NA,\ h\in NC_g \tag{7}$$

III. SOLUTION METHODOLOGY

To solve complex multi-objective and constraint-laden problems like Multi-Area Economic Emission Dispatch (MAEED), the real-coded NDSGA-II has been used in this study. The step-by-step workflow of the algorithm is described below in a simplified and structured manner:

Step-by-Step Process of NDSGA-II

1. Initialization: The algorithm begins by randomly generating an initial parent population (PAPOP) consisting of N1 members. These represent potential solutions to the optimization problem.

2. Fast Non-Dominated Sorting: Each solution in the population is ranked based on non-dominance. Solutions that are not dominated by any others are assigned to the first front (rank 1), the next set to the second front (rank 2), and so on. This helps prioritize better solutions during selection.

3. Tournament Selection: From the current population, two individuals are randomly selected and compared based on their front ranking and crowding distance (a measure of solution diversity). The better of the two is chosen and added to the mating pool.

4. Crossover and Mutation: Next, the mating pool undergoes Polynomial transmutation and Simulated Binary Crossover (SBX) to generate a new child population (CHPOP). This population is the same size (N1) as the parent population.

5. Merging of Populations: The parent (PAPOP) and child (CHPOP) populations are merged to create a combined population RESPOP of size 2N1.

6. Fast Non-Dominated Sorting on RESPOP: This combined population is then sorted again based on non-dominance. This step includes both parents and children, ensuring elitism (the best solutions are preserved). The algorithm selects the best individuals from the top fronts (starting with the first front, then second, and so on) until the new parent population reaches size N1.

If the number of individuals in the last front exceeds the required number of spots, solutions in that front are sorted based on crowding distance (in descending order), and the top solutions are selected to fill the remaining slots.

The result is a new generation of PAPOP containing N1 high-quality solutions.

7. *Repeat Until Termination*: The process—tournament selection → crossover → mutation → merging → sorting → selection—is repeated for a predefined number of generations. After each generation, the termination condition is checked.

If the stopping condition is not met, the newly created PAPOP is used as the parent for the next iteration.

8. Final Selection: Once the termination criterion is satisfied, the best solution is chosen from the first non-dominated front, representing the most optimal trade-off among objectives.

9. End of Execution: At this point, the NDSGA-II algorithm concludes.

A flowchart representing this entire process is shown in Figure I, followed by a detailed explanation.

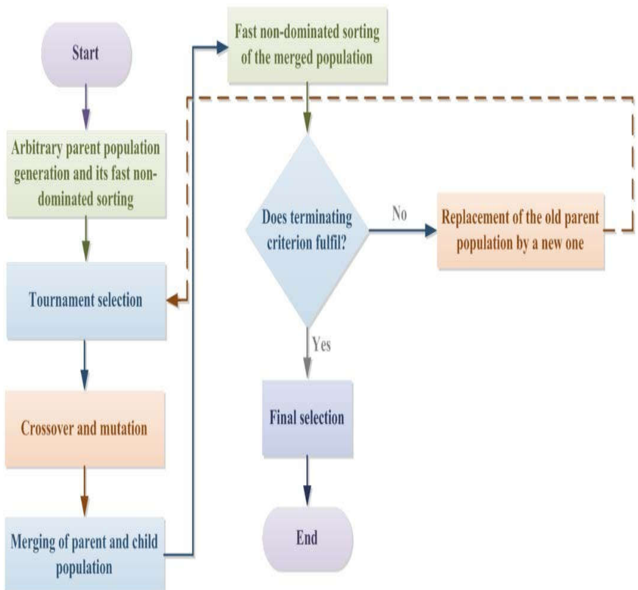

Fig. NDSGAII

$RES_{POP}= PA_{POP}\cup$ (Merging of the PA_{POP} and the CH_{POP})

- F_S denotes fast non-dominance based sorting (RES_{POP}).

  $F_S=\left(ND_{B1}, ND_{B2}, \ldots, ND_{Bl}\right)$

Where NDB_i denotes a non-dominance based front corresponding to the RES_{POP}.

  $PA_{POP}=\phi$ and $p = 1$

  Until $|PA_{POP}| + |FN_P| \leq N_1$ (i.e., the PA_{POP} fills)

- Assigning of $p_{dist}(FN_p)$

  $RES_{POP} = PA_{POP}\cup FN_p$ (Inclusion of p^{th} non-dominance based facade in the PA_{POP}) p = p + 1 (examination of the following front in order to include)

- Sorting (FNp,>)

  '>gets utilized for sorting in the decreasing order.

  $PA_{POP'} = PA_{POP'} \cup FN_p\left[1:\left(N_1- |PA_{POP}|\right)\right]$

Selecting the starting ($N_1 - |PA_{POP}|$) elements corresponding to FN_p.

$CH_{POP'}$ represents child population corresponding to the $PA_{POP'}$.

Figure II delineates flowchart of the STPEA II algorithm.

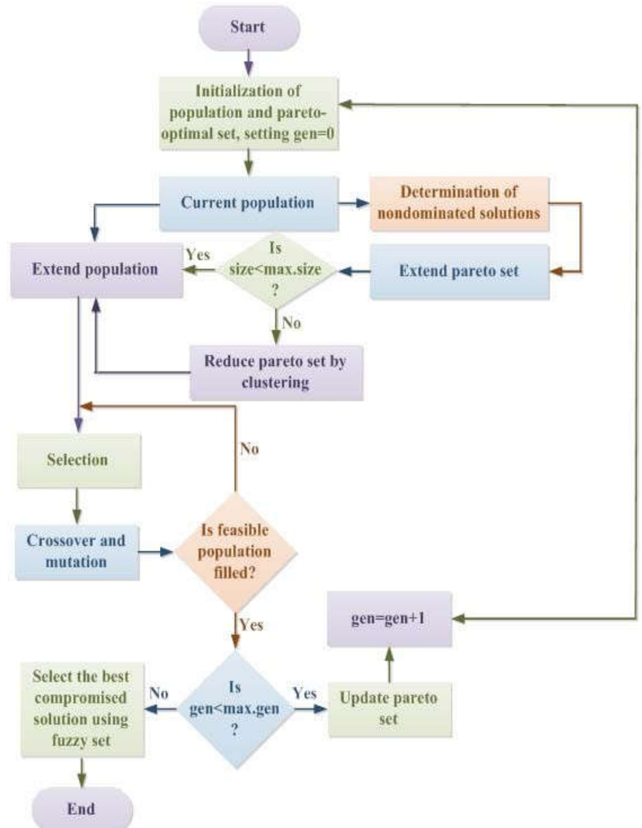

Fig. 2 SPEA II

IV. SIMULATION RESULTS

Evaluating NDSGA-II on a Multi-Area Power System: Performance and Comparisons: To demonstrate the effectiveness of the NDSGA-II, a four-area power system was used, with each area containing four generators. The model includes complex, non-smooth fuel cost functions and emission characteristics for pollutants. Detailed generator data and tie-line power exchange limits are provided in Appendix Tables A1 through A4. The load demands for areas 1 to 4 were set at 30 MWt, 50 MWt, 40 MWt, and 60 MWt, respectively.

The simulations were executed using custom-developed code in MATLAB R2013a. To determine the extreme points of the trade-off surface (between cost and emission), a real-coded genetic algorithm (RECGA) was used, based on the work by Herrera et al. (1998). Results showing area-wise power generation, associated operating costs, and emissions are visualized in Figures 3 through 6.

During the RECGA simulations, parameters were set as follows: population size = 100, number of generations = 500, mutation probability = 0.2, and crossover probability = 0.9. Under the cost-minimization objective, the fuel cost reached $1,521.92/hour with an emission level of 2.511944 tons/hour. When the focus shifted to minimizing emissions, the cost rose to $2,858.45/hour while emissions dropped to 2.255910 tons/hour. These trade-offs are further illustrated through the convergence curves in Figures 7 and 8.

To simultaneously optimize both cost and emissions, the NDSGA-II method was employed. For this scenario, the algorithm parameters were: population size = 20, generations = 50, mutation probability = 0.2, and crossover probability = 0.9. The results revealed a balanced outcome: fuel cost of $2,306.15/hour and emissions of 2.367206 tons/hour. These values lie between the extremes achieved when cost and emissions were optimized individually, demonstrating the method's effectiveness in achieving a good compromise.

To benchmark NDSGA-II's performance, another well-regarded method—Strength Pareto Evolutionary Algorithm II (STPEA-II)—was also applied to the same problem. Both algorithms were run with identical settings for a fair comparison: population size = 20, generations = 50, mutation = 0.2, crossover = 0.9.

Table I summarizes the best results from both NDSGA-II and STPEA-II, including the most cost-effective and least-polluting solutions, with RECGA results included for reference. Figure 9 presents 20 non-dominated solutions obtained at the final generation by both NDSGA-II and STPEA-II.

In Table II, the results from NDSGA-II are compared against those from other widely-used optimization techniques such as Particle Swarm Optimization (PSO), Differential Evolution (DE), and the Jaya Algorithm (JA), based on literature sources. Notably, the minimum fuel cost achieved by NDSGA-II was:

10.10% lower than PSO (Wang & Singh, 2009),

8.84% lower than DE (Pandit et al., 2015), and

8.80% lower than JA (Azizipanah-Abarghooee et al., 2016).

Similarly, the minimum emission level was reduced by:

28.03% compared to PSO,

5.98% compared to DE, and

4.84% compared to JA.

These significant improvements highlight the strength of NDSGA-II in solving complex multi-objective problems like MAEEDS. One of the key advantages of NDSGA-II is that it avoids favoring any single solution during its search process. Every solution on the Pareto front is treated with equal importance, which minimizes the chances of getting trapped in local optima. As a result, NDSGA-II is capable of uncovering superior solutions that other particle-based optimization methods might miss.

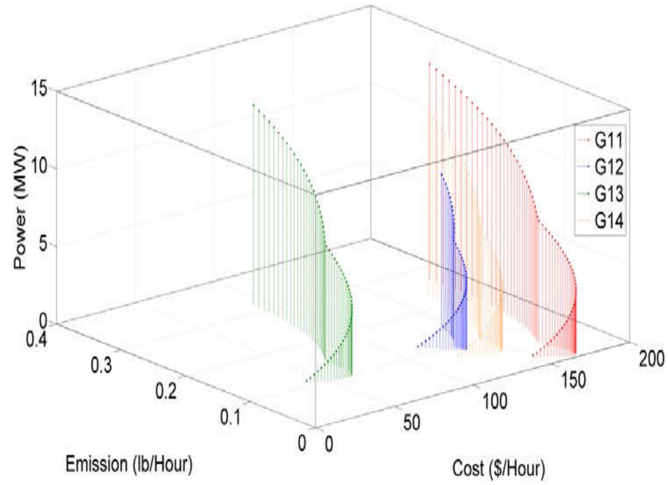

Fig. 3 Power/cost/emission character for area 1

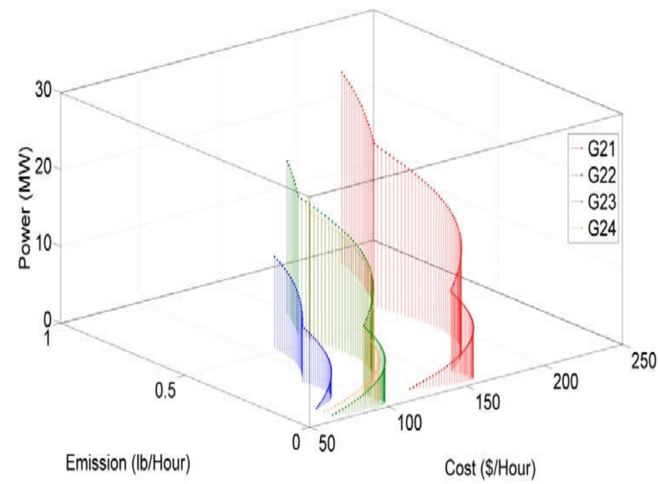

Fig. 4 Power/cost/emission character for area 2

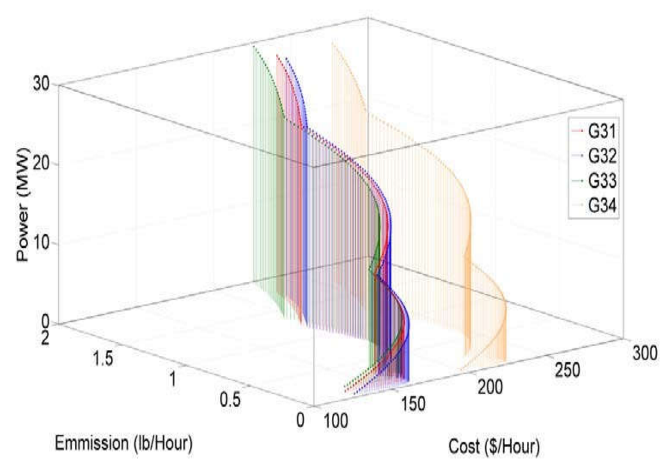

Fig. 5 Power-cost-emission characteristics for area 3 (see online version for colours)

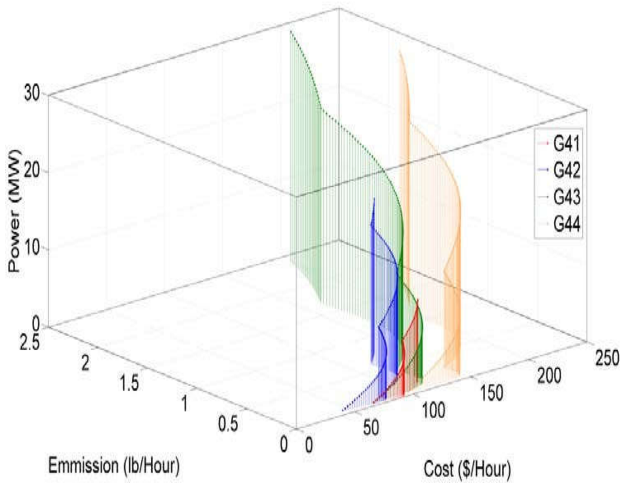

Fig. 6 Power/cost/emission character for area 4

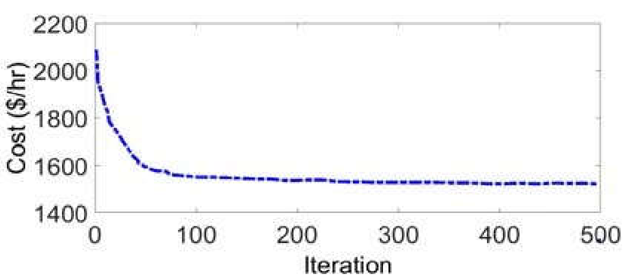

Fig. 7 Performance curve for the fuel cost

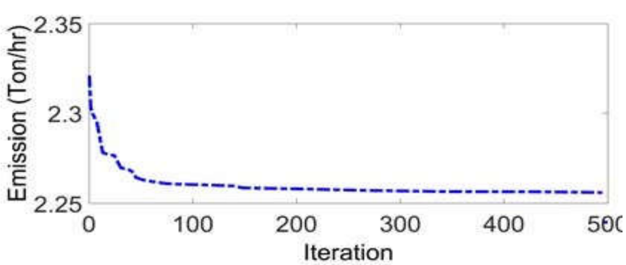

Fig. 8 Performance for the emission

TABLE 1 REPRODUCTION RESULTS

	Minimum fuel cost ($/hr)	*Minimum emission Level (Ton/hr)*	*NDSGA II*	*SPEA II*
P_{11} (MWt)	6.2199	0.000524	4.2767	3.7801
P_{12} (MWt)	0.0500	0.000450	2.4432	1.9565
P_{13} (MWt)	0.0675	0.117000	5.0288	9.0004
P_{14} (MWt)	11.6650	0.107682	10.2873	9.0604
P_{21} (MWt)	8.6814	0.225000	15.6294	13.9816
P_{22} (MWt)	0.3559	0.108000	9.1385	8.0030
P_{23} (MWt)	20.0000	0.084093	12.1516	17.5303
P_{24} (MWt)	17.9797	0.089201	16.1274	15.6876
P_{31} (MWt)	0.0500	0.084356	11.1128	14.2898
P_{32} (MWt)	30.0000	0.082287	11.5027	6.8935
P_{33} (MWt)	8.0818	0.107455	9.2512	3.3478
P_{34} (MWt)	10.0555	0.115771	11.5776	18.2130
P_{41} (MWt)	1.4822	0.099000	7.8041	7.1157
P_{42} (MWt)	14.0633	0.151746	14.1608	13.0403
P_{43} (MWt)	30.0000	0.129198	21.1647	18.8948
P_{44} (MWt)	21.2478	0.118237	18.3432	19.2051
T_{21} (MWt)	6.0000	0.054000	4.4186	4.3529
T_{13} (MWt)	–3.9976	–0.006468	–2.5100	–1.5756
T_{41} (MWt)	2.0000	–0.016125	1.0355	0.2741
T_{32} (MWt)	3.5000	0.031500	1.4146	1.0910
T_{24} (MWt)	–5.4830	0.033794	0.0429	1.9407
T_{34} (MWt)	0.6898	–0.008100	–0.4802	0.0775

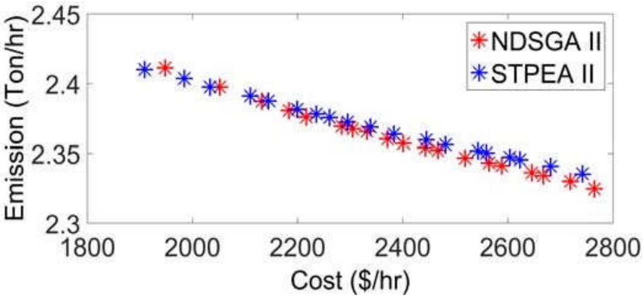

Fig. 9 Final optimal pareto

TABLE II RELATIVE ANALYSIS

Optimizers	*Economic dispatch*	
	Minimum generation cost ($/hr)	*Corresponding emission level (Ton/hr)*
PSO (Wang and Singh, 2009)	2,166.82	3.3152
DE (Pandit etal, 2015)	2,136.95	6.5383
JA (Azizipanah-Abarghooee etal, 2016)	2,135.99	5.8157
NDSGAII	1,948.08	2.4100
STPEAII	1,909.12	2.4112
Optimizers	*Emission dispatch*	
	Minimum emission level (Ton/hr)	*Corresponding generation cost ($/hr)*
PSO (Wang and Singh, 2009)	3.2301	2,178.20
DE (Pandit et al., 2015)	2.4725	2,178.28
JA (Azizipanah-Abarghooee et al., 2016)	2.4429	2,177.55
NDSGA II	2.3247	2,764.54
STPEA II	2.3355	2,741.85

V CONCLUSIONS

Strategy of MAEED is a critical optimization challenge in power system operations. This study proposes the use of the Non-Dominated Sorting Genetic Algorithm II (NDSGA-II) to address this bi-objective problem—minimizing both fuel cost and emissions—across a four-area power network, while accounting for real-world constraints such as load-generation balance, generator capacity, and tie-line transmission limits.

A detailed comparison between the results obtained using NDSGA-II, Strength Pareto Evolutionary Algorithm II (STPEA-II), and other established methods highlights the effectiveness of both NDSGA-II and STPEA-II for solving such dual-objective optimization tasks. Among these, NDSGA-II demonstrates superior performance in achieving better trade-off solutions in this particular setup.

However, it's important to recognize that the true global optimal solution for complex MAEEDS problems is generally unknown. Real-world systems often involve more areas, diverse constraints, and non-linear characteristics, making it uncertain whether the same algorithm will consistently perform best across all scenarios.

Therefore, while this work validates NDSGA-II for the chosen case, future research should focus on testing and developing newer, more advanced multi-objective optimization algorithms on a wider range of MAEEDS models. Exploring their adaptability and robustness in more complex, real-world configurations will be key to advancing this field

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APPENDIX

TABLEA1 GENERATOR CHARACTERISTICS (PRODUCTION CAPACITY LIMITS)

Generator (GNgh)	$P_{gh}^{min}(MWt)$	$P_{gh}^{max}(MWt)$
GN_{11}	0.05	14
GN_{12}	0.05	10
GN_{13}	0.05	13
GN_{14}	0.05	12
GN_{21}	0.05	25
GN_{22}	0.05	12
GN_{23}	0.05	20
GN_{24}	0.05	18
GN_{31}	0.05	30
GN_{32}	0.05	30
GN_{33}	0.05	30
GN_{34}	0.05	30
GN_{41}	0.05	11
GN_{42}	0.05	20
GN_{43}	0.05	30
GN_{44}	0.05	30

TABLEA2 GENERATOR CHARACTERISTICS (COST COEFFICIENTS)

Generator(GNgh)	a_{gh}*(\$/hr)*	b_{gh}*(\$/MWt.hr)*	c_{gh}*(\$/MWt2.hr)*	d_{gh}*(\$/hr)*	e_{gh}*(rad/MWt)*
GN_{11}	0	38.53900	0.15247	100	0.084
GN_{12}	0	46.15916	0.10587	150	0.063
GN_{13}	0	40.39655	0.02803	120	0.077
GN_{14}	0	38.30553	0.03546	200	0.042
GN_{21}	0	36.32782	0.02111	300	0.035
GN_{22}	0	38.27041	0.01799	150	0.063
GN_{23}	0	2.000000	0.00375	18.0	0.037
GN_{24}	0	1.750000	0.01750	16.0	0.038
GN_{31}	0	3.000000	0.02500	13.5	0.041
GN_{32}	0	2.000000	0.00375	18.0	0.037
GN_{33}	0	1.000000	0.06250	14.0	0.040
GN_{34}	0	1.750000	0.01950	15.0	0.039
GN_{41}	0	3.250000	0.06250	12.0	0.045
GN_{42}	0	3.250000	0.00834	12.0	0.045
GN_{43}	0	1.750000	0.01950	15.0	0.039
GN_{44}	0	1.000000	0.00834	14.0	0.040

TABLEA3 GENERATOR CHARACTERISTICS (EMISSION COEFFICIENTS)

Generator (GNgh)	α_{gk} *(Ton/hr)*	β_{gk} *(Ton/MWt.hr)*	γ_{gk} *(Ton/MWt^2.hr)*	η_{gk} *(Ton/hr)*	δ_{gk} *(MWt^{-1})*
GN_{11}	0.124734	0.002949	0.000037	0.011790	0.05690
GN_{12}	0.124734	0.002949	0.000037	0.008228	0.04540
GN_{13}	0.362402	–0.004910	0.000061	0.008942	0.04060
GN_{14}	0.362402	–0.004910	0.000061	0.005895	0.02846
GN_{21}	0.386060	–0.004600	0.000041	0.004532	0.02075
GN_{22}	0.386060	–0.004600	0.000041	0.008228	0.04540
GN_{23}	0.368190	–0.000500	0.000058	0.000002	0.00285
GN_{24}	0.022887	–0.000544	0.000051	0.000005	0.00333
GN_{31}	0.055179	–0.000500	0.000046	0.000000	0.00666
GN_{32}	0.031419	–0.000518	0.000058	0.000003	0.00265
GN_{33}	0.038322	–0.000458	0.000041	0.000000	0.00800
GN_{34}	0.024786	–0.000526	0.000047	0.000004	0.00287
GN_{41}	0.047934	–0.000320	0.000030	0.000020	0.00200
GN_{42}	0.047934	–0.000320	0.000030	0.000020	0.00200
GN_{43}	0.024786	–0.000526	0.000047	0.000004	0.00287
GN_{44}	0.038322	–0.000458	0.000041	0.000000	0.00800

TABLEA4 TIE LINE POWER TRANSFERRING CAPACITY LIMITS

Tie line (T_{go})	$-T_{go}^{\max}$ (MWt)	$T_{go}^{\max}$ (MWt)
T_{12}	–6.0	6.0
T_{13}	–4.0	4.0
T_{14}	–2.0	2.0
T_{23}	–3.5	3.5
T_{24}	–5.5	5.5
T_{34}	–0.9	0.9