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Economical-Environmental-Technical Operation of Power Networks with High Penetration of Renewable Energy Systems Using Multi-Objective Coronavirus Herd Immunity Algorithm

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Abstract: This paper proposes an economical-environmental-technical dispatch (EETD) model for adjusted IEEE 30-bus and IEEE 57-bus systems, including thermal and high penetration of renewable energy sources (RESs). Total fuel costs, emissions level, power losses, voltage deviation, and voltage stability are the five objectives addressed in this work. A large set of equality and inequality constraints are included in the problem formulation. Metaheuristic optimization approaches—Coronavirus herd immunity optimizer (CHIO), salp swarm algorithm (SSA), and ant lion optimizer (ALO)—are used to identify the optimal cost of generation, emissions, voltage deviation, losses, and voltage stability solutions. Several scenarios are reviewed to validate the problem-solving competency of the defined optimisation model. Numerous scenarios are studied to verify the proficiency of the optimisation model in problem-solving. The multi-objective problem is converted into a normalized one-objective issue through a weighted sum-approach utilizing the analytical hierarchy process (AHP). Additionally, the technique for order preference by similarity to ideal solution (TOPSIS) is presented for identifying the optimal value of Pareto alternatives. Ultimately, the results achieved reveal that the proposed CHIO performs the other approaches in the EETD problem-solving.

Keywords: analytical hierarchy process (AHP); economical-environmental-technical dispatch; Coronavirus herd immunity optimizer (CHIO); renewable energy sources (RESs); TOPSIS

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1. Introduction

Using renewable energy sources (RESs) in conventional power grids is difficult since renewables have a stochastic nature. The expansion of the use of RES technologies has also shown that conventional thermal production plants face technoeconomic challenges. These challenges are of major significance if we are to overcome the complexities of renewable energy planning and facilitate seamless renewable integration of electricity grids that integrates the stochastic nature of photovoltaics, wind, and hydropower. To justify the investments in RES technologies, the grid must operate economically with a high level of dependability. In the sense of the climate [1], thermal stations emit many pollutants, including nitrogen oxides, carbon oxides, sulphur dioxides, and others [2]. Moreover, reduced network capacity losses, improved energy efficiency [3], voltage support, and investments will improve the power system operations. The formulation of the economical-environmental-technical dispatch (EETD) model will address this problem.
In the literature, the conventional economic, environmental, and technical dispatch problem was addressed by many traditional techniques, which were used to address optimization techniques, such as linear and quadratic iterative techniques \[4\], lambda iterating approaches \[5\], and gradient methods \[6\]. Since it is challenging to identify global solutions at a sufficient estimation period (computation time) because of the EETD problem’s intricacy, most of these initiatives encountered challenges \[7\]. The researchers, therefore, sought to implement updated formulations of influential mathematical optimization approaches, such as mixed-integer linear (MIL) and quadratic (MIQ) programming type \[8\], nonlinear (NL) programming \[9\], and dynamics programming (DP) \[10,11\], to address the EETD issue. Many traditional mathematical optimization methods offered significant challenges when dealing with large-scale generation-incorporated power systems. They were frequently tipped into local minima because their preference coefficients appeared to vary through the optimization processes, which enhanced the estimation period considerably.

Recently, various metaheuristic optimization methods have been used in the literature, with and without the inclusion of the RESs for coping with the above-stated deficiencies of single objective (SO) and multi-objective (MO) functions \[12,13\]. Several evolutionary and metaheuristic optimisation methods have been used to effectively address the EETD problem, for instance: particle swarm optimization (PSO) through time-varying accelerating constant so-named TVAC-PSO \[14\]; accelerating PSO (APSO) \[14\]; modified MO moth-flame optimizer (MFO) \[15\]; modified whale optimization algorithm (MWOA) \[16\]; the internal search algorithm (ISA) \[17\]; criss-cross optimizer (CCO) \[18\]; a mixture of salp swarm optimizer (SSA) and PSO \[19\]; MO differential evolutionary based on summation (SMODE) \[20\]; enhanced SSA (ESSA) \[21,22\]; artificial bee colony (ABC) based on dynamic population, so-named ABC-DP \[23\], ABC \[24\]; MO population exterior optimizer (MOPEO) \[25\]; MO cross-entropy optimizer built on decomposition (MOCEO/D) \[26\]; and symbiotic organisms search (SOS) optimizer \[27\], as seen in Table 1.

Some have considered RESs, and some have not considered them while solving their problem of optimizations. Table 1 lists many recent research studies that have explored the role of RESs in the classical issue of EETD. Duman et al. \[27\] proposed the SOS technique to minimize cost functions, real power losses, voltage deviation, enhancement of contingency circumstances, and voltage stability. That approach was examined through IEEE 30-bus and IEEE 118-bus through incorporating RESs of wind, solar, and tidal energies. However, some constraints, such as prohibited operating zones (POZs) and valve point impacts, were not involved in the problem. Chen et al. \[25\] proposed the MOPEO technique for reducing costs and emissions for the IEEE 30-bus scheme and the inclusion of thermal, wind, and solar generating modules. The paper \[28\] proposed the NSGA-II with the reinforcement learning process, known as NSGA-RL, used to solve the MOEETD problems. The formulas for optimizing fuel costs and emissions were presented to include six thermal units incorporating the wind-power units. The results revealed that the NSGA-RL technique is successful in solving multi-objective EETD problems. However, it could be preferable to utilize more than one RES, such as solar or tidal power. The paper \[20\] introduced MOEA/D and SMODE techniques to minimize emission and cost functions in the IEEE 30-bus scheme, including the uncertainties of wind-, solar-, and tidal-power-producing units to address the MOEETD issue with a restricted number of thermal units. The paper \[29\] presented the thermal-, wind-, solar-, and tidal-power systems with a complex day-ahead stochastic scheduling, but only the cost of the fuel was involved in the optimization process. Elattar \[30\] proposed an enhanced shuffled-frog leaping-optimizer (ESFLO) to lessen fuel costs and emissions for MOEETD in combined power and heat units, with regard to the attendance of wind and solar power. Chinnadurrai and Victoire \[18\] presented a multi-objective CCO technique to minimize cost and emission functions with uncertain wind-energy units. That approach employed conventional multi-objective test functions and then ordinary complex EETD issues concerned with various wind-power integration ratios. The paper \[31\] proposed an enhanced sine cosine optimizer (ESCO) to solve different issues of EETD problems, such as costs, voltage profile, and power losses as a SO function.
Li et al. [32] presented the MOCHIO approach for solving dynamic EETD of hybrid RESs built on green certifications, although some limits increasing power flow were not explored in the problem. Table 1 lists some of the most recent studies on the presence and absence of RESs.

Table 1. Review of single and multi-objective EETD of thermal units in the presence and absence of RESs.

| System                  | Ref. | IEEE System       | Algorithms         | Objective Functions | Decision-Making Tools |
|-------------------------|------|-------------------|---------------------|---------------------|-----------------------|
|                         |      | 30-Bus            |                     |                     |                       |
|                         |      | 57-Bus            |                     |                     |                       |
|                         |      | 118-Bus           |                     |                     |                       |
| IEEE without RESs       | [26] | ✓                 | ✓                   | MOCE/D              |                       |
|                         | [31] | ✓                 | -                   | ESCA                | ✓                     |
|                         | [33] | ✓                 | -                   | MOFA-CPA            | -                     |
|                         | [34] | ✓                 | -                   | MOMICA              | -                     |
|                         | [35] | ✓                 | ✓                   | I-NSGA-III          | -                     |
|                         | [36] | ✓                 | -                   | ECHT                | -                     |
|                         | [37] | ✓                 | ✓                   | DA-PSO              | -                     |
|                         | [38] | ✓                 | -                   | SPEA                | -                     |
|                         | [39] | ✓                 | -                   | TLBO                | -                     |
|                         | [40] | ✓                 | ✓                   | KHA                 | -                     |
|                         | [41] | ✓                 | -                   | PSO                 | -                     |
|                         | [42] | ✓                 | ✓                   | MSA                 | -                     |
| IEEE integrated with RESs| [13] | ✓                 | -                   | MOHHO               | -                     |
|                         | [20] | ✓                 | -                   | MOEA/D & SMODE      | -                     |
|                         | [25] | ✓                 | -                   | MOPEO               | -                     |
|                         | [26] | ✓                 | -                   | NSGA-RL             | -                     |
|                         | [43] | ✓                 | -                   | GSA                 | -                     |
|                         | [44] | ✓                 | -                   | FFA & MGA           | -                     |
|                         | [45] | ✓                 | -                   | SMODE               | -                     |
|                         | [46] | ✓                 | -                   | MOEA/D              | -                     |
|                         | [47] | ✓                 | -                   | PIRO                | -                     |
|                         | [48] | ✓                 | -                   | NSGA-II             | -                     |
|                         | [49] | ✓                 | -                   | PSO                 | -                     |
|                         | [50] | ✓                 | -                   | EFPA & FFPA         | -                     |
|                         | [51] | ✓                 | -                   | GABC                | -                     |
|                         | [52] | ✓                 | -                   | SSA & IGWO          | -                     |
| Proposed                |      | ✓                 | ✓                   | CHIO & ALO & SSA    | ✓                     |

In this study, the IEEE 30-bus and IEEE 57-bus schemes are amended for integrating photovoltaic (PV), wind power (WP), and tidal power (TP) plants with a constrained number of thermal generations. The PV, WP, and TP uncertainties are discussed in-depth, utilizing suitable probability density functions (PDFs)—lognormal, Weibull, and Gumbel, respectively. The cost models presented in this study discuss the volatility and intermittent nature of the RESs, including underestimation of the penalty cost (UPC) and overestimation of the reservation cost (ORC). A Coronavirus herd immunity optimizer (CHIO), a salp swarm algorithm (SSA) [53], and an ant lion optimizer (ALO) [54] are employed as multi-objective and SO optimization approaches to identify the production cost as an economic benefit, emissions as an environmental benefit, losses ($P_{\text{loss}}$), voltage deviation (VD), and stability index ($L$-index) as a technical benefit. Various conditions are examined to demonstrate the suggested mode’s potential to meet this challenge. Moreover, a weighting sum policy utilizing the analytical hierarchy process (AHP) can be utilized for converting the MOEETD issue into a normalised SOEETD. In addition, as a single solution may be supported by the decision maker, the technique for order preference by similarity to the ideal solution (TOPSIS) classification tool was used to find a single alternative from the non-dominated solutions group of problems under survey. In the calculation process, the benefits of a TOPSIS measuring tool are consistency, simplicity, and understandability.

This article’s contributions are summarized as follows:
- Expression of the SOEETD and MOEETD problem considering thermal, PV, WP, and PVTP plants (integration of high penetration of various RESs) is investigated.
- Stochastic study of high penetration of RESs addressed has been accessible utilizing the appropriate PDFs.
- Various system restrictions including security, equality, inequality, and POZs constraints are investigated in the presented EETD problem.
• Various optimization approaches, such as the CHIO, the ALO, and the SSA, with a comprehensive study of the solutions are used to solve the EETD problem.
• The AHP is utilized to convert MOEETD into the SOEETD problem.
• The TOPSIS is applied for obtaining the optimum alternative for the MOEETD issue.

The rest of the paper is structured as follows: The formation of the systems of SOEETD and MOEETD is demonstrated in Section 2. Section 3 describes the mathematical model of the high penetration of RESs, the formulation of SO and MO objectives, and the conception of limitations. Section 4 presents the recommended optimization strategies. The results are examined and discussed in Section 5. Lastly, Section 6 presents conclusions and future works.

2. Systems Investigated and Scenarios Studies

The first phase of this study is the development of ideal location buses for RESs. The design criteria to find the best location of RESs is corresponding to the optimum EETD issue when the PV, WP, and PVTP are inserted on all buses one by one. The optimal power flow (OPF) is used to add PV panels one by one, starting with bus two and working through all the buses in each system. The bus with the lowest cost for 24 h is the best candidate for PV panels. The OPF is also used to optimize the site of WP and PVTP using the same method as the PV panel optimal sitting as long as the PV panels are installed on the previously selected buses. The capacities of these plants are selected to be consistent with the test systems’ maximum demands. The simulation results of this phase, which are the ideal location for the RESs for each of IEEE 30-bus and IEEE 57-bus testing schemes, are presented in Table 2. These locations of RESs are employed in the EETD problem, and the next step of this study is the uncertainties of RESs and are given in detail in the next section.

| Table 2. Optimal location of the RESs in the IEEE 30-bus and IEEE 57-bus schemes. |
|-------------------------------|-----------|-----------------|
| **Systems** | **IEEE30-Bus** | **IEEE57-Bus** |
| Photovoltaic (PV) | Bus 11 | Bus 3 |
| Wind (WP) | Bus 5 | Bus 2 |
| PV + Tidal power (PVTP) | Bus 13 | Bus 9 |

This work integrates both traditional thermal stations and non-conventional RESs that address the IEEE 30-bus and IEEE 57-bus schemes. As depicted in Figure 1, various significant RESs of PVs, wind, and hybrid PVs and tidal power (PVTP) schemes for the IEEE 30-bus are tied on buses 11, 5, and 13, respectively. In addition, the RESs of PVs wind and PVTP for the IEEE 57-bus are tied on buses 3, 2, and 9, respectively. The IEEE 30-bus system also includes three thermal power generations (TPGs) tied on buses 1, 2, and 8. In addition, the IEEE 57-bus scheme includes four TPGs tied on buses 1, 6, 8, and 12. The necessary system’s specifications are described in Table 3.

| Table 3. Parameters of the IEEE30-bus and IEEE57-bus systems [55]. |
|------------------|------------------|------------------|------------------|------------------|
| **Elements** | **Quantity** | **Parameters** | **Quantity** | **Parameters** |
| Generators | 6 | 3 TPGs and 3 RESs | 7 | 4 TPGs and 3 RESs |
| TPGs | 3 | Buses 1(swing), 2, and 8 | 4 | Buses 1 (swing), 6, 8, and 12 |
| PV | 25 | Bus 11, 75 MW | 75 | Bus 3, 175 MW |
| WP | 1 | Bus 5, 50 MW | 1 | Bus 2, 90 MW |
| PVTP | 1 | Bus 13, 45 + 5 MW | 1 | Bus 9, 75 + 15 MW |
| Static VAR compensator | 9 | Buses 10, 12, 15, 17, 20, 21, 23, 24, and 29 | 3 | Buses 18, 25, and 53 |
| Load connected (P and Q) | - | 283.40 MW and 126.20 MVAr | - | 1250.80 MW and 336.40 MVAr |
| Number of PQ buses | 24 | 24 buses | 50 | 50 buses |
| Load voltage permissible range (pu) | - | 0.950–1.10 | - | 0.950–1.10 |
Figure 1. The systems under study: (a) IEEE 30-bus; and (b) IEEE 57-bus.

The second phase of this work has 16 scenarios, and their descriptions are seen in Table 4. These scenarios are classified by test procedure and each system’s number...
of objectives. The first scheme will present 13 case studies: the IEEE 30-bus system. In scenarios 14 to 16, the second scheme of the IEEE 57-bus will be introduced. These scenarios represent one and MOs that indicate different economic, environmental, and technical issues.

Table 4. Description of SOEETD and MOEETD formulation.

| Test System | EETD Formulation | Economical | Environmental | Technical |
|-------------|------------------|------------|---------------|-----------|
|              | No. of Objective Functions | Scenario | Fuel Costs | Emissions | VD | $P_{loss}$ | $L_{Max}$ |
| IEEE-30     | 1                | 1         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 2                | 2         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 3                | 3         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 4                | 4         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 5                | 5         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 6                | 6         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 7                | 7         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 8                | 8         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 9                | 9         | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 10               | 10        | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 11               | 11        | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 12               | 12        | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 13               | 13        | ✓           | ✓         | ✓ | ✓ | ✓ |
| IEEE-57     | 1                | 14        | ✓           | ✓         | ✓ | ✓ | ✓ |
|             | 2                | 15        | ✓           | ✓         | ✓ | ✓ | ✓ |
|             |                  | 16        | ✓           | ✓         | ✓ | ✓ | ✓ |

3. Formulation of the Optimization Problems

The EETD issue is implemented by simultaneously minimizing numerous computing objectives—fuel costs, emissions, voltage deviation, power losses, and enhancement of line index ($L$-index)—taking into account various constraints. In general, the EETD issue can be outlined as the following:

\[ J_{obj} = \min \sum_{i=1}^{N_{obj}} J_i(x, v) \]  

Subject to

\[ g_k(x, v) = 0 \quad k = 0, 1, \ldots, G \]  
\[ h_l(x, v) \leq 0 \quad l = 0, 1, \ldots, L \]

where \( J_{obj} \) represents the objectives to be minimized. \( J_1, J_2, J_3, J_4, \) and \( J_5 \) represent the quanta-objectives to be minimized. They represent the fuel costs, emissions, voltage deviation, losses, and \( L \)-index, respectively. \( x \) signifies the state (dependent) variables, and \( v \) represents the control variables. \( g_k(x, v) \) and \( h_l(x, v) \) represent the \( k \)th equality constraints and the \( l \)th inequality constraints, respectively.

3.1. Total Fuel Costs

The total costs of the produced powers are the sum of costs of the TPGs and RESs, as expressed in Equation (4).

\[ J_1(x, v) = C_{tot}(P_{TPGs}) + C_{tot}(P_{RESs}) \]  

where \( C_{tot}(P_{TPGs}) \) denotes the total TPGs cost, and \( C_{tot}(P_{RESs}) \) denotes the total RESs cost.

3.1.1. Fuel-Cost Study of TPG Units

The costs of TPGs in $/MWh depend more on the blades’ steam flow of the turbine and the unpredicted fluctuations in a valve’s position. In such plants, a series of valves push steam through a scattered set of nozzles that are used to deliver good output in full
production [39]. The valves are sequentially opened for compulsory output, resulting in the interruption costs curve, as seen in Figure 2. Equation (5) provides the cost formulation of TPGs [30].

\[ C_{\text{tot}}(P_{\text{TPG}}) = \sum_{i=1}^{N_{\text{TPG}}} a_{\text{TPG}} + b_{\text{TPG}} P_{\text{TPG}} + c_{\text{TPG}} P_{\text{TPG}}^2 + |d_i \sin(e_i (P_{\min}^{\text{TPG}} - P_{\text{TPG}}))| \]  

(5)

where \( N_{\text{TPG}} \) denotes the number of thermal generator units. \( a_{\text{TPG}}, b_{\text{TPG}}, \) and \( c_{\text{TPG}}, d_i, e_i \) denote the cost coefficients of the ith thermal generator unit (\( P_{\text{TPG}} \)). The two coefficients \( d_i \) and \( e_i \) denote the impact’s valve point. \( P_{\min}^{\text{TPG}} \) denotes the minimum powers of \( P_{\text{TPG}} \) through the generator operations. These parameters are described in Table 5.

![Figure 2](image.png)

**Figure 2.** The cost of fuel functions with and without the effect of valve point.

**Table 5.** Emission and cost coefficients for IEEE 30-bus and IEEE 57-bus of the TPGs [30].

| Generators | Bus | \( \varphi_{\text{TPG}} \) (t/h) | \( \psi_{\text{TPG}} \) (t/pu-MW\text{h}) | \( \omega_{\text{TPG}} \) (t/\text{pu-MW}^2\text{h}) | \( \tau_{\text{TPG}} \) (t/h) | \( \xi_{\text{TPG}} \) (\text{pu-MW}^{-1}) |
|------------|-----|-------------------------------|-----------------------------|-----------------------------|----------------|-----------------|
| **IEEE 30-bus** | | | | | | |
| TPG1 | 1 | 0.04092 | -0.05553 | 0.0649 | 0.0003 | 6.668 |
| TPG2 | 2 | 0.02543 | -0.06048 | 0.05639 | 0.0006 | 3.334 |
| TPG3 | 8 | 0.05327 | -0.0356 | 0.0339 | 0.003 | 2.0 |
| **IEEE 57-bus** | | | | | | |
| TPG1 | 1 | 4.091 | -5.554 | 6.49 | 0.0002 | 0.286 |
| TPG2 | 6 | 2.543 | -6.047 | 5.638 | 0.0005 | 0.333 |
| TPG3 | 8 | 6.131 | -5.55 | 5.151 | 0.0001 | 0.667 |
| TPG4 | 12 | 3.491 | -5.754 | 6.39 | 0.0003 | 0.266 |

| Generators | Bus | \( a_{\text{TPG}} \) ($/h) | \( b_{\text{TPG}} \) ($/MW\text{h}) | \( c_{\text{TPG}} \) ($/MW^2\text{h}) | \( d_{\text{TPG}} \) ($/h) | \( e_{\text{TPG}} \) (MW^{-1}) |
|------------|-----|----------------------------|-----------------------------|-----------------------------|----------------|-----------------|
| **IEEE 30-bus** | | | | | | |
| TPG1 | 1 | 30 | 2 | 0.00377 | 18 | 0.038 |
| TPG2 | 2 | 25 | 1.76 | 0.0176 | 16 | 0.039 |
| TPG3 | 8 | 20 | 3.26 | 0.0833 | 12 | 0.046 |
| **IEEE 57-bus** | | | | | | |
| TPG1 | 1 | 0 | 20 | 0.0775795 | 18 | 0.037 |
| TPG2 | 6 | 0 | 40 | 0.01 | 16 | 0.038 |
| TPG3 | 8 | 0 | 20 | 0.02222 | 13.5 | 0.041 |
| TPG4 | 12 | 0 | 20 | 0.03226 | 18 | 0.037 |
3.1.2. Fuel-Cost Study of the RESs

The cost’s RESs are the sum of the overall costs of WPs \( C_{\text{tot}}(P_{WP}) \), PVs \( C_{\text{tot}}(P_{PV}) \), and hybrid PV and PVTP \( C_{\text{tot}}(P_{PVTP}) \), which can be expressed as shown in Equation (6):

\[
C_{\text{tot}}(P_{\text{RESs}}) = C_{\text{tot}}(P_{WP}) + C_{\text{tot}}(P_{PV}) + C_{\text{tot}}(P_{PVTP})
\]

(6)

However, there is a cost feature for each renewable source. The sum of energy that is undersupplied or oversupplied may also be estimated relying on the PDFs of each source. First, standby power-generating (SPG) units may be mounted to meet the intermittent nature of the RESs while the produced power is lower than the power scheduled. Second, energy storage (ES) could be mounted to store the additional power produced [56].

In accordance with random wind speed, solar irradiance, and tidal unit flow rate results, Weibull, lognormal, and Gumbel distributions are used to convey the cost terms as seen as follows.

Cost estimation of WPs \( C_{\text{tot}}(P_{WP}) \) : \( C_{\text{tot}}(P_{WP}) \) is described by merging the investment costs \( C_{\text{inv}}(P_{WP_{sch}}) \) directly besides storage units’ costs and the SPGs. \( C_{\text{inv}}(P_{WP_{sch}}) \) denotes the costs of operation and maintenance as follows:

\[
C_{\text{inv}}(P_{WP_{sch}}) = K_{\text{inv}} P_{WP_{sch}}
\]

(7)

where \( K_{\text{inv}} \) signifies the direct cost coefficient, and \( P_{WP_{sch}} \) signifies the WPs’ power scheduled. The scheme also could involve possible standby elements to conserve the demand desires, and this reserve cost capacity \( C_{r_{wp}} \) can be expressed as follows:

\[
C_{r_{wp}}(P_{WP_{act}} - P_{WP_{sch}}) = K_{r_{wp}}(P_{WP_{act}} - P_{WP_{sch}}) = K_{r_{wp}} \int_{P_{WP_{sch}} - P_{WP_{act}}}^{P_{WP_{act}}} (P_{WP_{sch}} - P_{WP}) f_{WP}(P_{WP}) dP_{WP}
\]

(8)

where \( K_{r_{wp}} \) signifies the cost coefficient of the standby elements, and \( P_{WP_{act}} \) signifies the real WPs’ power delivered. \( f_{WP}(P_{WP}) \) denotes the wind PDF. \( P_{WP_{sch}} \) represents the WGs’ supplied power. Similarly, if \( P_{WP_{sch}} < P_{WP_{act}} \); also, the ES’ cost \( C_{r_{wp}} \), described in (9), should be appended to the WP cost. The cost factors of WPs can be expressed in Appendix A.

\[
C_{\text{inv}}(P_{WP_{act}} - P_{WP_{sch}}) = K_{\text{inv}}(P_{WP_{act}} - P_{WP_{sch}}) = K_{\text{inv}} \int_{P_{WP_{sch}}}^{P_{WP_{act}}} (P_{WP_{act}} - P_{WP_{sch}}) f_{WP}(P_{WP}) dP_{WP}
\]

(9)

The WGs’ supplied power that be dependent on \( v \) is expressed as follows:

\[
p_{WP} = \begin{cases} 
0 & v_{out} \leq v \leq v_{in} \\
\frac{v - v_{in}}{v_{r} - v_{in}} & v_{in} \leq v \leq v_{r} \\
1 & v_{r} \leq v \leq v_{out} 
\end{cases}
\]

(11)

where \( v_{in}, v_{out}, v_{r} \) correspond to the WPs’ cut-in, cut-out, and rated speeds, respectively. The probability’s WP \( f_{WP}(P_{WP}) \) is given in (12).

\[
f_{WP}(P_{WP}) = \frac{\beta(v_{r} - v_{in})}{\alpha \beta P_{WP}} \left[ v_{in} + P_{WP} \frac{v_{r} - v_{in}}{P_{WP} + P_{WP}} \right]^{\beta - 1} \exp \left[ -\left( v_{in} + \frac{P_{WP}}{P_{WP}} (v_{r} - v_{in}) \right) \right]^\beta
\]

(12)
To sum up, $C_{tot}(P_{WP})$ is expressed in (13).

$$C_{tot}(P_{WP}) = C_{dpv}(P_{WP_{sch}}) + C_{rwp}(P_{WP_{act}} - P_{WP_{act}}) + C_{swp}(P_{WP_{act}} - P_{WP_{sch}})$$  

Cost estimation of the PV ($C_{tot}(P_{PV})$): As well, the WPs’ cost function, the direct cost $C_{dpv}(P_{PV_{sch}})$ of PVs signifies the costs of operation and maintenance and can be described as follows:

$$C_{dpv}(P_{PV_{sch}}) = K_{dpv}P_{PV_{sch}}$$

where $K_{dpv}$ denotes the direct cost parameter, and $P_{PV_{sch}}$ signifies the scheduled power of PV.

Once $P_{PV_{sch}}$ is superior to the PV system’s real power ($P_{PV_{act}}$), it is crucial to calculate SPGs, as clarified previously. The PV’s cost reserve capacity ($C_{rpv}$) may appear if $P_{PV_{sch}} < P_{PV_{act}}$, and this is expressed in (16).

$$C_{rpv}(P_{PV_{act}} - P_{PV_{sch}}) = K_{rpv}(P_{PV_{act}} - P_{PV_{sch}}) = K_{rpv}(P_{PV_{sch}} - p_{PV})f_{PV}(p_{PV})$$

$K_{rpv}$ signifies the cost coefficient of the SPGs. $f_{PV}(p_{PV})$ denotes the PV-PDF. $p_{PV}$ represents the PVs’ supplied power. Moreover, the cost of storage units ($C_{spv}$) may appear as follows:

$$C_{spv}(P_{PV_{act}} - P_{PV_{sch}}) = K_{spv}(P_{PV_{act}} - P_{PV_{sch}}) = K_{spv}(P_{PV} - P_{PV_{sch}})f_{PV}(p_{PV})$$

The cost parameters of PV can be additionally offered in Appendix A. The power provided from the backup and ES units depends on the solar irradiance ($G$) PDF, represented as $f_{PV}(G)$. Lognormal fitting (LF) [59,60] can be frequently utilized to obtain $f_{PV}(G)$, as depicted in Figure 3b for 8000 Monte-Carlo turns at lognormal fit parameters: $\mu = 5.6$ and $\sigma = 0.6$. Consequently, $f_{PV}(G)$ is expressed as follows:

$$f_{PV}(G) = \frac{1}{G\sigma\sqrt{2\pi}} \exp \left\{ -\frac{(\ln G - \mu)^2}{2\sigma^2} \right\}, \quad \forall G > 0$$

The attainable PV’s power ($p_{PV}(G)$) can be assessed as follows

$$p_{PV}(G) = \begin{cases} 
    p_{PVr}\left(\frac{G^2}{G_{std}^2}\right), & 0 < G < R_c \\
    p_{PVr}\left(\frac{G}{G_{std}}\right), & G \geq R_c 
\end{cases}$$

where $G_{std}$ signifies the traditional solar irradiance, and $R_c$ signifies the operation irradiance, wherein $G_{std} = 1000$ W/m$^2$, and $R_c = 120$ W/m$^2$. $p_{PVr}$ signifies the PVs rated power output. To summarize, $C_{totpv}$ can be described as follows:

$$C_{tot}(P_{PV}) = C_{dpv}(P_{PV_{sch}}) + C_{spv}(P_{PV_{act}} - P_{PV_{sch}}) + C_{rpv}(P_{PV_{sch}} - P_{PV_{act}})$$

Cost estimation of the PVTP plant ($C_{tot}(P_{PVTP})$): Gumbel fitting (GF) [61] is employed in the river flow’s fitting of ($Q_w$) statistics, as displayed in Figure 3c, wherein $f_Q(Q_w)$ traces the GD through coefficients $\lambda$ and $\gamma$ as the following:

$$f_Q(Q_w) = \frac{1}{\gamma} \exp \left( \frac{Q_w - \lambda}{\gamma} \right) \exp \left[ -\exp \left( \frac{Q_w - \lambda}{\gamma} \right) \right]$$

The yield power from the tidal power plant $P_I(Q_w)$ relies on $Q_w$ as expressed in (19):

$$P_I(Q_w) = \eta_wq_wg_wQ_wH_w$$

where $\eta_w$, $g_w$, $q_w$, and $H_w$ signify the tidal efficiency turbines’, the gravity acceleration, the density’s water, and the operational head pressure, respectively [62], wherein $\eta_w = 0.86$;
\[ \rho_w = 1000 \text{ kg/m}^3; g_w = 9.81 \text{ m/s}^2; \text{ and } H_w = 26 \text{ m.} \] At this bus, the TP unit is incorporating through a PV unit to enhance the TP station operation. To summarize, \( C_{\text{tot PVTP}} \) can be illustrated as follows:

\[
C_{\text{tot PVTP}}(P_{PVTP sch}) = C_{dPVTP}(P_{PVTP sch}) + C_{rPVTP}(P_{PVTP sch} - P_{PVTP act}) + C_{sPVTP}(P_{PVTP act} - P_{PVTP sch})
\]

where \( P_{PVTP sch} \) and \( P_{PVTP act} \) signify the hybrid PVTP’s scheduled and real powers, respectively. \( C_{dPVTP}(P_{PVTP}) \) signifies the PVTP direct cost. The PVTP’s cost reserve capacity can be denoted as \( (C_{rPVTP}) \). The storage units cost of the PVTP system can be denoted as \( (C_{sPVTP}) \). The cost parameters of PVTP can be described in Appendix A.

Furthermore, the whole cost of the arrangement can be described as follows:

\[
J_1(x, v) = \sum_{i=1}^{N_{TPC}} a_{TPG_i} v + b_{TPG_i} v + c_{TPG_i} v^2 + \left| d_i \sin(e_i (p_{\text{min}}_{TPG_i} - P_{TPG_i})) \right| + C_{dWP}(P_{WP sch}) + C_{rWP}(P_{WP sch} - P_{WP act}) + C_{sWP}(P_{WP act} - P_{WP sch}) + C_{dPV}(P_{PV sch} - P_{PV act}) + C_{rPV}(P_{PV sch} - P_{PV act}) + C_{sPV}(P_{PV act} - P_{PV sch}) + C_{dPVTP}(P_{PVTP sch}) + C_{rPVTP}(P_{PVTP sch} - P_{PVTP act}) + C_{sPVTP}(P_{PVTP act} - P_{PVTP sch})
\]

\[ (23) \]

**Figure 3.** Measured PDFs of WP, PV irradiance, and tidal: (a) WF; (b) LF; and (c) GF.
3.2. Emission Levels

Only the emission levels of TPGs \( \left( E_{\text{tot}} \right) \) are addressed because the RESs have few to no pollutant gases, as given in (24):

\[
J_2(x, v) = E_{\text{tot}} = \sum_{i=1}^{N_{\text{TPG}}} \left[ \varphi_{\text{TPG}_i} + \psi_{\text{TPG}_i} P_{\text{TPG}_i} + \omega_{\text{TPG}_i} P_{\text{TPG}_i}^2 + \tau_{\text{TPG}_i} \xi_{\text{TPG}_i} P_{\text{TPG}_i} \right] \tag{24}
\]

where \( E_{\text{tot}} \) signifies the overall emissions of the \( i \)th TPG. \( \varphi_{\text{TPG}_i}, \psi_{\text{TPG}_i}, \omega_{\text{TPG}_i}, \tau_{\text{TPG}_i}, \) and \( \xi_{\text{TPG}_i} \) are the coefficients of pollutant emissions related to the \( i \)th TPGs and are tabulated in Table 5.

3.3. Voltage Deviation

The fourth goal is to minimize the voltage deviations \( (\Delta V) \) that could be described as follows:

\[
J_3(x, v) = \Delta V = \sum_{i=1}^{N_{\text{bus}}} \left| V_i - 1 \right| \tag{25}
\]

where \( V_i \) and \( N_{\text{bus}} \) indicate \( i \)th bus voltages and the number of buses, respectively.

3.4. Power Losses

The third goal is to lessen the real losses \( (P_{\text{loss}}) \) of the electric utility that can be described as follows:

\[
J_4(x, v) = P_{\text{loss}} = \sum_{i=1}^{N_G} \left[ V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_{ij}) \right] \tag{26}
\]

where \( N_G \) denotes the number of generator buses. \( V_i \) and \( V_j \) correspond to \( i \) and \( j \) bus voltages, respectively. \( \delta_{ij} = \delta_i - \delta_j \) signifies the voltage phase shift variation between \( i \) and \( j \) buses.

3.5. Voltage Stability Metric

To improve system’s voltage stability, it intends to lessen the maximum voltage stability index \( (L-\text{index}) \) that is described by Equations (27) and (28):

\[
J_5(x, v) = L-\text{index} = \left| 1 - \sum_{i=1}^{N_G} F_{ij} \frac{V_i}{V_j} \right| (\theta_{ij} + \delta_i - \delta_j) \tag{27}
\]

\[
F_{ij} = -|Y_{LL}|^{-1} |Y_{LG}| \tag{28}
\]

3.6. Constraints

The limitations judged while implementing the OP can be summarized as the following.

3.6.1. Power Balance

The restrictions to stabilize the real and reactive powers through the total load powers consumed and the losses of the power can be expressed as the following:

\[
P_{\text{TPG}} = P_{L_i} + P_{\text{Loss}_i} \tag{29}
\]

\[
Q_{\text{TPG}} = Q_{L_i} + Q_{\text{Loss}_i} \tag{30}
\]

3.6.2. Limits of the Active and Reactive Powers

The operation limits for active and reactive powers of the TPGs, WPs, PVs, and PVTP are expressed as follows:

\[
P^\text{min}_{\text{TPG}_i} \leq P_{\text{TPG}_i} \leq P^\text{max}_{\text{TPG}_i} \quad \forall \ i \in N_{\text{TPG}} \tag{31}
\]
\[ P_{WP}^{\min} \leq P_{WP} \leq P_{WP}^{\max} \]  
(32)

\[ P_{PV}^{\min} \leq P_{PV} \leq P_{PV}^{\max} \]  
(33)

\[ P_{PVTP}^{\min} \leq P_{PVTP} \leq P_{PVTP}^{\max} \]  
(34)

\[ Q_{TPG_i}^{\min} \leq Q_{TPG_i} \leq Q_{TPG_i}^{\max} \quad \forall \ i \in N_{TPG} \]  
(35)

\[ Q_{WP}^{\min} \leq Q_{WP} \leq Q_{WP}^{\max} \]  
(36)

\[ Q_{PV}^{\min} \leq Q_{PV} \leq Q_{PV}^{\max} \]  
(37)

\[ Q_{PVTP}^{\min} \leq Q_{PVTP} \leq Q_{PVTP}^{\max} \]  
(38)

### 3.6.3. Limits of POZs

POZs, the aim for cutting off in the process of the TPGs, can be described in (39):

\[ P_{TPG_i}^{\min POZ,j} \leq POZ_{TPG_i}^j \leq P_{TPG_i}^{\max POZ,j} \]  
(39)

where \( P_{TPG_i}^{\min POZ,j} \) and \( P_{TPG_i}^{\max POZ,j} \) signify the minimum and maximum boundaries (MW) of the \( j \)th POZ of the \( i \)th TPG.

### 3.6.4. Security Restrictions

The generators and voltage at load buses’ boundaries can be described in (40) and (41), respectively. In addition, the thermal limits can be considered as follows:

\[ V_{G_i}^{\min} \leq V_{G_i} \leq V_{G_i}^{\max} \quad \forall \ i \in N_{G} \]  
(40)

\[ V_{L_j}^{\min} \leq V_{L_j} \leq V_{L_j}^{\max} \quad \forall \ j \in N_{L} \]  
(41)

\[ S_{L_j} \leq S_{L_j}^{\max} \quad \forall \ j \in n_l \]  
(42)

where \( V_{G_i}, V_{L_j} \) denote the \( i \)th’s generator bus voltage and the \( j \)th’s load bus voltage, respectively. \( N_{G}, N_{L}, \) and \( n_l \) indicate the generator buses, load buses, and branches numbers, respectively.

Multi-objective problems may be subjected to linear, nonlinear, equality, and inequality constraints. The inequality constraints of other variables are included in the objective functions using a death penalty factor (\( P \)) by adding an extremely high value to the objective functions to avoid infeasible solutions (when a solution violates a constraint, it will be rejected). \( P \) is set to \( 10^8 \) in the optimization problem investigated.

### 4. Coronavirus Herd Immunity Optimizer (CHIO)

Mathematically, the notion of herd protection can be modeled to build the fundamental CHIO technique [63]. The methodological approach depends on the notion that humanity protects against infection by changing the majority of the non-infected vulnerable to immune [64]. Consequently, the protected population will no longer propagate this virus; even those vulnerable instances would not be harmed. The populations of people with herd protection could be categorized into resistant, susceptible, and infectious. The CHIO formulation is built on the population of the herd protection as shown in Figure 4. The improvement technique is derived from susceptible, contaminated, and immunized persons in the execution method of the CHIO technique. With the CHIO algorithm, the definition of societal distance is achieved by splitting the individual from the community that may be vulnerable, diseased, or protected between the present individual and a particular individual. The method to herd protection is based on the CHIO methodology. The algorithm is developed in six main phases. The technique for implementation is as follows.
Rule #1: Set CHIO parameter—The CHIO objective function is:

$$\min f(x), \quad x \in [lb, ub]$$  \hspace{1cm} (43)$$

where for all the individuals, the objective function is created, in which the variable of decision is $x_i$, and indexed with “i”, and the gene number in everyone is indicated as $n$. The CHIO approach needs dual control factors, such as maximum diseased cases age ($Max_{Age}$) and fundamental reproduction rate ($BR_i$), and four algorithmic factors, such as $C_0 (=1)$, $Max_{Iter}$ represents maximum iteration number, $HIS$ represents the size of herd immunity, and $n$ indicates size.
Rule #2: Generate herd immunity populations (HIP)—Originally, the CHIO generates heuristically a number of persons such as HIS. As a bidimensional matrix, the created individuals are kept in the HIP as follows:

\[
HIP = \begin{bmatrix}
    x_1^1 & \cdots & x_n^1 \\
    \vdots & \ddots & \vdots \\
    x_1^{HIS} & \cdots & x_n^{HIS}
\end{bmatrix}
\]

For each person, the best solution is derived using Equation (44). The status trajectory \(S\) is also determined by either zero or one for all individuals in the HIP. Please note that \(S\) numbers are randomly begun up to \(C_0\).

Rule #3: Herd immunity evolution—It is the principal upgrade loop of CHIO. The individual gene gives the same or publicly differentiated influence, according to the BR, by using three principles:

\[
x_i^{j}(t+1) = \begin{cases}
    x_i^{j}(t), & r \geq BR_r \\
    C(x_i^{j}(t)), & r < 0.333 \times BR_r \text{ (Infected)} \\
    N(x_i^{j}(t)), & r < 0.667 \times BR_r \text{ (Susceptible)} \\
    R(x_i^{j}(t)), & r < BR_r \text{ (Immuned)}
\end{cases}
\]

where \(r\) signifies an arbitrary number from \([0, 1]\). The diseased situation is in the range of 0 to \(0.333 \times BR_r\). The importance of the latest gene can be diminished by societal distance and can be obtained by the differences among the genes from the diseased situation and the present gene as the following.

\[
x_i^{j}(t+1) = C(x_i^{j}(t))
\]

\[
C(x_i^{j}(t)) = x_i^{j}(t) + r \times (x_i^{j}(t) - x_i^{j}(t))
\]

Similarly, the susceptible case can be in the range of \(0.333 \times BR_r\) to \(0.667 \times BR_r\). In addition, the safe case is in the range of \(0.667 \times BR_r\) to \(BR_r\).

Rule #4: Population update—The protection rate can be computed for each produced instance, but the existing alternative will only be replaced through the produced issue if \(f(x_i^{j}(t+1)) < f(x_i^{j}(t))\). If the status vector \(S_i\) is equally one, the age vector \((A_j)\) is incremented to one. The values of \(S_j\) are changed by the following equation throughout each cycle, according to the herd immunologic threshold.

\[
S_j = \begin{cases}
    1, & f(x_i^{j}(t+1)) < \frac{f(x_i^{j}(t+1))}{A_j(x)} \wedge S_j = 0 \wedge is\_Corona(x_i^{j}(t+1)) \\
    2, & f(x_i^{j}(t+1)) < \frac{f(x_i^{j}(t+1))}{A_j(x)} \wedge S_j = 1
\end{cases}
\]

where \(is\_Corona(x_i^{j}(t+1))\) is equally one, that is a binary quantity when a new situation has taken advantage of infected cases.

Rule #5: Casualty cases—If the protection rate of the present afflicted case might not arise for the required iteration, as provided in the \(Max\_{Age}\) parameter, then this process is deemed dead. It is then regenerated from the scratched utilizing \(x_i^{j}(t+1) = lb_j + (u lb_j - lb_j) \times U(0, 1)\). In addition, the values of \(S_j\) and \(S_i\) are set to be zero. It could help the current population to increase and hence avoid optimal local alternatives.

Rule #6: Stopping rank—The CHIO is implemented in Rules 3 to 5 until the stop requirement has been fulfilled, usually in accordance with the maximum number of iterations \((Max\_itr)\). The total amount of protected and susceptible cases in this condition...
dominates the population. The infected case will also be eliminated. The CHIO algorithm’s flow diagram is shown in Figure 5.

Figure 5. CHIO algorithm’s flowchart [64].

4.1. Implementation Procedure of Multi-Objective CHIO

The implementation of the presented CHIO approach can be provided as follows.

1. Set the CHIO parameters; Max\_itr = 300; Max\_Age = 100; popsize (HIS) = 50; C₀ = 1; BRₗ = 0.05; lb and ub are given in each table in results.
2. Assess the immunological position of herd X using the Pareto sorting algorithm.
3. Obtain the non-dominated solution of the objective function as given in Equations (23), (25)–(28) together or individually, according to the implemented scenario.
4. Collect them in the Pareto archive and determine the crowding space for every archive member.
5. The Pareto sorting system is utilized for assessing the best person (non-dominated solution alone) in the archive, removing dominated alternatives from the archive.
6. The population located in the CHIO method is modernized with Equation (49).
7. Modernize the iteration cycle t to t = t + 1.
8. Return to Rule #2 if t is less than Max\_itr. The actual positions will be assessed and the ideal Pareto front S_X will be returned.
9. Find the best solutions for the Pareto sorting system.
10. Using a TOPSIS to obtain the one alternative that might be preferred through with the decision maker to speed up and integrate several possibilities as illustrated in the next Section 4.3.
11. In addition, we can use the AHP to obtain the weighting factors with the CHIO technique to transform MO into SO function 4.2.

4.2. Analytical Hierarchy Process

Once the variety of difficulties of engineering rises, because of the trade-offs, the single objective inquiry is no longer an excellent solution. Increasing the objective value
of a design may impair the performance of other objectives if several choices are offered. It can be utilized for multi-objective issues and techniques. However, several optimum spots on the Pareto graph that suit the criteria of decision makers three or four objectives, are not enough. This means that the decision maker might occasionally obtain one of Pareto’s most obvious questions to repeatedly look at all problems of interest. The AHP becomes one of the most often utilized techniques in decision making as well as provides numerous advantages among the multiple processes with various dimensions and features: simplicity, adjustability, and transparency that permit comparison and assessment of distinct possibilities. In the majority of cases, the main strategy to implementation of a priority setting is to discover the most viable solution [65].

The standard AHP procedure is summed up in [52]—building the model of hierarchal ranking; forming the judgment matrix; evaluating the maximum value of your own ($\lambda_{max}$), and the corresponding judgmental vector in which the elements of the vector reflect the relative factor weights and the “hierarchical ranking” and confirm the precision of the AHP with the consistency indices ($CI$) that should be less than 10%.

$$M = \begin{bmatrix} 1 & \psi_{12} & \psi_{13} & \psi_{14} \\ \frac{1}{\psi_{12}} & 1 & \psi_{23} & \psi_{24} \\ \frac{1}{\psi_{13}} & \frac{1}{\psi_{23}} & 1 & \psi_{34} \\ \frac{1}{\psi_{14}} & \frac{1}{\psi_{24}} & \frac{1}{\psi_{34}} & 1 \end{bmatrix}, \forall m, n \in N$$

where, $\psi_{mn} \in \{1, 3, 5, 7, 9\}$. $N$ represents the number of the sub-objectives.

The consistency indices ($CI$) can be evaluated as follows:

$$CI = \frac{\lambda_{max} - N_j}{N_j - 1}$$

It can also evaluate the consistency ratio ($CR$), as the following:

$$CR = \frac{CI}{RI}$$

$N_j$ and $RI$ signify the judgment matrix dimension and the average random index, respectively. For further information about the AHP, please see [66–68].

The objectives are set corresponding to their relevance for the decision maker in this circumstance. In Egypt, the quality of the voltage is the priority based on the perspective of the energy suppliers and should meet national regulations. The main aim for network operators is to reduce fuel costs in the present period. The secondary objective is active power loss minimization. They are the third priority, notwithstanding the significance of reducing pollution levels.

The objective functions cannot be immediately merged into the solution due to their differing dimensions. As a result, the objective functions were normalized as follows:

$$\min_x \left( \frac{J_1(x)}{J_{10}} + \frac{J_2(x)}{J_{20}} + \frac{J_3(x)}{J_{30}} + \frac{J_4(x)}{J_{40}} + \frac{J_5(x)}{J_{50}} \right)$$

where $J_{10}$, $J_{20}$, $J_{30}$, $J_{40}$, and $J_{50}$ represent the designer threshold values of the objective functions (maximum values). $w_1$, $w_2$, $w_3$, $w_4$, and $w_5$ are the weighting factors of fuel costs, emissions, $VD$, $P_{loss}$, and $L$-index, respectively. Then, the weights are calculated as follows:

$$\varphi_m = \sum_{n=1}^{NF} \psi_{mn}, \forall m, n = 1, 2, 3, 4$$

$$w_m = \frac{\varphi_m}{\sum_{n=1}^{N} \varphi_n}$$
In this work, the objective functions for Scenarios from 6 to 13 in the IEEE 30-bus system and for Scenarios 15 and 16 in the IEEE 57-bus are implemented using the AHP. Table 6 illustrates the judgment matrix and the weights of the EETD problem.

### Table 6. The judgment matrix and the weights.

| System     | Scenario | Judgment Matrix (M) | Weights |
|------------|----------|---------------------|---------|
|            | 6        | $M = \begin{bmatrix} 1 & 2 \\ 0.5 & 1 \end{bmatrix}$ | $w_1 = 0.6667$ $w_2 = 0.3333$ |
|            | 7        | $M = \begin{bmatrix} 1 & 2 \\ 0.5 & 1 \end{bmatrix}$ | $w_1 = 0.6667$ $w_3 = 0.3333$ |
|            | 8        | $M = \begin{bmatrix} 1 & 2 \\ 0.5 & 1 \end{bmatrix}$ | $w_1 = 0.6667$ |
|            | 9        | $M = \begin{bmatrix} 1 & 2 & 2 \\ 0.5 & 1 & 1 \\ 0.5 & 0.5 & 1 \end{bmatrix}$ | $w_1 = 0.5$ $w_3 = 0.25$ $w_4 = 0.25$ |
|            | 10       | $M = \begin{bmatrix} 1 & 2 & 2 \\ 0.5 & 1 & 1 \\ 0.5 & 0.3 & 1 \end{bmatrix}$ | $w_1 = 0.44118$ $w_2 = 0.39706$ $w_4 = 0.16176$ |
|            | 11       | $M = \begin{bmatrix} 1 & 2 & 2 \\ 0.5 & 1 & 1 \\ 0.5 & 0.3 & 1 \end{bmatrix}$ | $w_1 = 0.34711$ $w_2 = 0.27273$ $w_3 = 0.27273$ $w_4 = 0.10744$ |
|            | 12       | $M = \begin{bmatrix} 1 & 2 & 2 & 2 \\ 0.5 & 1 & 1 & 1 \\ 0.5 & 0.1 & 1 & 1 \\ 0.5 & 0.3 & 0.3 & 1 \end{bmatrix}$, | $w_1 = 0.29032$ $w_2 = 0.20968$ $w_3 = 0.20968$ $w_4 = 0.080642$ |
|            | 13       | $M = \begin{bmatrix} 1 & 2 & 2 & 2 \\ 0.5 & 1 & 1 & 1 \\ 0.5 & 0.1 & 1 & 1 \\ 0.5 & 0.3 & 0.3 & 1 \end{bmatrix}$ | $w_1 = 0.29032$ $w_2 = 0.20968$ $w_3 = 0.20968$ $w_4 = 0.080642$ $w_5 = 0.080642$ |
|            | 15       | $M = \begin{bmatrix} 1 & 2 \\ 0.5 & 1 \end{bmatrix}$ | $w_1 = 0.6667$ $w_3 = 0.3333$ |
|            | 16       | $M = \begin{bmatrix} 1 & 2 \\ 0.5 & 1 \end{bmatrix}$ | $w_1 = 0.6667$ $w_2 = 0.3333$ |

In progression, the judgment matrix and the weights are identified in this study, as illustrated in Table 6.

### 4.3. A Technique for Order Preference by Similarity to Ideal Solution

To compare Pareto with the optimization methods, just one alternative might be preferred through the decision maker to speed up and integrate several possibilities. Ranking or classification processes can be utilized to provide several non-dominant solutions. This work uses a classified approach called TOPSIS to resolve this variance in decision making with multi-attributes decision making (MADM) [69].

A TOPSIS manages to realize the best alternative that should include the quickest time from the positive–ideal alternative and the farthest time from the negative–ideal alternative. The major purpose of using a TOPSIS is to make computations coherent, understandable, and straightforward. The positive solution from all the best attributes and the negative alternative from all the worst attributes are generated by this procedure. A TOPSIS works
based on euclidean space computation to the ideal alternative [13]. The TOPSIS approach was used to classify the specific Pareto solutions achieved by the optimizations utilized. The primary premise of a TOPSIS is to discover an alternative that should be the smallest possible length from the ideal positive solution ($H^+$) and the longest from the ideal negative alternative ($H^-$).

In this study, the most important and smallest index change is the positive ideal solution ($H_{ij}^+$), while the opposite solution is the negative ideal solution ($H_{ij}^-$). The TOPSIS method is synthesized in these steps:

**Rule #1:** Define a decision matrix $X$. The value $F_{ij}$ denotes a hint for the performing ranking of the $i$th choice regarding the $j$th function. Let, $S = (s_1, s_2)$ be the relative weighted trajectory of the objectives, fulfilling $\sum_{j=1}^{n} s_j = 1$.

**Rule #2:** Define the normalized value $Z_{ij}$ by employing Equation (55):

$$Z_{ij} = \frac{F_{ij}}{\sqrt{\sum_{i=2}^{n} F_{ij}^2}} \forall i = 1, 2, \ldots, n & j = 1, 2$$ (55)

**Rule #3:** Determine $M_{ij}$ applying Equation (56) that signifies the weighted normalized decision matrix.

$$M_{ij} = s_j \times Z_{ij} \forall i = 1, 2, \ldots, n & j = 1, 2$$ (56)

**Rule #4:** Obtain $H_{ij}^+$ and $H_{ij}^-$ using Equations (57) and (58):

$$H_{ij}^+ = \{\min(M_{11}, \ldots M_{1n}), \min(M_{12}, \ldots M_{n2})\}$$ (57)

$$H_{ij}^- = \{\max(M_{11}, \ldots M_{1n}), \max(M_{12}, \ldots M_{n2})\}$$ (58)

**Rule #5:** Utilizing the $n$-dimensional euclidean space, define the split procedures through Equations (59) and (60):

$$S_{ij}^+ = \sqrt{\sum_{i=2}^{n} (M_{ij} - H_{ij}^+)^2} \forall i = 1, 2, \ldots, n & j = 1, 2$$ (59)

$$S_{ij}^- = \sqrt{\sum_{i=2}^{n} (M_{ij} - H_{ij}^-)^2} \forall i = 1, 2, \ldots, n & j = 1, 2$$ (60)

**Rule #6:** Evaluate the relative closeness ($RC_{ij}$) to the ideal solution, which can be expressed as in Equation (61):

$$RC_{ij} = \frac{S_{ij}^-}{S_{ij}^+ + S_{ij}^-} \forall i = 1, 2, \ldots, n & j = 1, 2$$ (61)

**Rule #7:** The preference order is to be rated so that the best compromise alternative can be considered as the alternative with the ultimate $RC$ to the ideal alternative. Figure 6 shows the AHP implementation flowchart.

4.4. Implementation Procedure of EETD Problem

The implementation of the presented algorithms, including the AHP and the TOPSIS, can be summarized as follows:

1. Set the input data of TPGs and RESs; WP, PV, and PVTP as given in Table 3 in addition to the parameters of RESs.
2. Load the test systems of IEEE 30-bus and IEEE 57-bus from MATPOWER in Matlab.
3. Formulate the objective functions for SOEETD and MOEETD problems.
4. The AHP is employed with the MOEETD problem to obtain the weighting factors.
5. Set the algorithm’s parameters—maximum number of iterations, search agents, . . . etc.
6. Assess the decision variables; the active powers and voltage profiles buses, as illustrated in Tables A3 and A4.
7. Set the system constraints, as illustrated in Section 3.6.
8. Obtain the non-dominated solutions of the OFs.
9. Use a TOPSIS to obtain the best solution from the Pareto sorting system.

[Diagram]

Figure 6. The AHP implementation flowchart.

The implementation of the presented algorithms, including the AHP and the TOPSIS, are depicted in Figure 7.
The implementation of the presented algorithms, including the AHP and TOPSIS, are depicted in Figure 7.

Figure 7. The implementation procedure of the EETD problem, including AHP and TOPSIS, techniques.

5. Results and Discussion

5.1. Results of IEEE 30-Bus Scheme

For SO and MO scenarios for this test scheme, the simulation findings are stated as follows:

5.1.1. Single Objective Scenarios

Tables 7 and 8 outline the details of the EETD simulation of Scenarios 1–5 with the three competitive optimization techniques: the CHIO, the ALO, and the SSA. It can be
noted, as shown in Table 7, that the lower and upper bounds are presented in the third and fourth columns. For instance, control variables are scheduled for Scenarios 1–3. The primary SOEETD utilizing three mentioned optimization approaches (in bold for each case) and the remaining objectives are described in Table 8.

Table 7. Lists of control variables for Scenarios 1–3 for IEEE 30-bus test scheme.

| Variables and Parameters | Scenario #1 | Scenario #2 | Scenario #3 |
|--------------------------|-------------|-------------|-------------|
| Min | Max | CHIO | ALO | SSA | CHIO | ALO | SSA | CHIO | ALO | SSA |
|---|---|---|---|---|---|---|---|---|---|---|
| Active power | $P_{TPG}$ | 20 | 80 | 37.445 | 46.634 | 46.634 | 46.634 | 80 | 53.655 | 60.324 |
| Reactive power | $Q_T$ | 30 | 60 | 0.96 | 1.1341 | 1.1341 | 1.1341 | 1.1341 | 1.1341 | 1.1341 |
| Bus voltage (pu) | $V$ | 1.1 | 0.1025 | 1.025 | 0.9926 | 1.0054 | 1.0054 | 1.0054 | 1.0054 | 1.0054 |
| Wind power (MW) | $P_{w}$ | 115.61 | 115.21 | 115.21 | 115.21 | 115.21 | 115.21 | 115.21 | 115.21 | 115.21 |
| PV power (MW) | $P_{PV}$ | 109.88 | 110.42 | 110.42 | 110.42 | 110.42 | 110.42 | 110.42 | 110.42 | 110.42 |
| PVTP power (MW) | $P_{PVTP}$ | 96.68 | 97.61 | 97.61 | 97.61 | 97.61 | 97.61 | 97.61 | 97.61 | 97.61 |
| Fuel costs ($/h) | $\text{Fuel}\_\text{cost}$ | 447.54 | 454.04 | 454.04 | 454.04 | 454.04 | 454.04 | 454.04 | 454.04 | 454.04 |
| Fuel costs ($/h) | $W_{gang}$ | Not applicable | 115.61 | 115.21 | 115.21 | 115.21 | 115.21 | 115.21 | 115.21 | 115.21 |
| Emissions (ton/h) | $E_{\text{emissions}}$ | 0.15187 | 0.15187 | 0.15187 | 0.15187 | 0.15187 | 0.15187 | 0.15187 | 0.15187 | 0.15187 |
| Computation time (s) | $\text{Computation}\_\text{time}$ | 367.206 | 364.553 | 364.553 | 364.553 | 364.553 | 364.553 | 364.553 | 364.553 | 364.553 |

Table 8. Results of SOEETD problem using three optimization techniques for IEEE 30-bus (Scenarios 1–5).

| Scenarios | Optimizations | Fuel costs ($/h) | Emissions (ton/h) | $VD$ (pu) | $P_{loss}$ (MW) | $L$-Index |
|-----------|---------------|------------------|------------------|-----------|-----------------|-----------|
| Scenario #1 | CHIO | 768.95 | 0.15187 | 1.1341 | 5.54 | 0.11186 |
| | ALO | 769.32 | 0.15363 | 1.1054 | 5.6165 | 0.11136 |
| | SSA | 769.64 | 0.15086 | 0.90473 | 5.6392 | 0.12337 |
| Scenario #2 | CHIO | 848.89 | 0.09055 | 0.74422 | 4.2397 | 0.18187 |
| | ALO | 850.48 | 0.09055 | 0.83431 | 4.6292 | 0.19684 |
| | SSA | 856.14 | 0.09055 | 0.95844 | 5.9606 | 0.2305 |
| Scenario #3 | CHIO | 867.01 | 0.10619 | 0.36824 | 4.4902 | 0.0799 |
| | ALO | 826.36 | 0.0987 | 0.3779 | 4.6292 | 0.19684 |
| | SSA | 852.4 | 0.0988 | 0.3771 | 5.9627 | 0.2305 |
| Scenario #4 | CHIO | 895.88 | 0.10281 | 1.3265 | 2.0661 | 0.1013 |
| | ALO | 911.08 | 0.10922 | 1.3251 | 4.0724 | 0.10073 |
| | SSA | 872.76 | 0.095233 | 1.322 | 4.0848 | 0.10155 |
| Scenario #5 | CHIO | 911.81 | 0.10833 | 1.3251 | 2.6828 | 0.071587 |
| | ALO | 913.04 | 0.10822 | 1.3251 | 2.6828 | 0.071587 |
| | SSA | 911.05 | 0.10792 | 1.3251 | 2.667 | 0.071596 |

In Scenario 1, minimization of the fuel costs is the major objective function (OF). The proposed CHIO technique offers the lowest cost (USD 768.95/h) compared with USD 769.32/h, USD 769.64/h obtained by ALO and SSA, respectively. In Scenario 2, minimization of the emission levels is the main OF. The proposed techniques: the CHIO, the ALO, and the SSA have achieved the minimum emission levels (0.09055 ton/h) that comply with environmental aspects. In Scenario 3, minimization of the $VD$ is the main OF. The proposed CHIO technique has the least voltage deviation (0.36824 pu) in comparison to ALO and SSA techniques, the presented CHIO offers an improved voltage profile. In Scenario 4,
minimization of the $P_{\text{loss}}$ is the main OF. The power losses are decreased by the presented approaches, the CHIO, the ALO, and the SSA, and their estimates become 2.0661 MW, 2.0724 MW, and 2.0848 MW, respectively. In Scenario 5, the $L$-index is minimized for improving the system stability. The quantities of $L$-index of the presented optimization approaches, the CHIO, the ALO, and the SSA equal 0.071587, 0.071614, and 0.071596, respectively.

Notably, the proposed CHIO indicates the best power loss reduction 2.0661 MW, the most economical alternative USD 768.95/h, and the improved voltage profile ($V_D = 0.36824$ pu). In addition, the CHIO tends to have the least voltage stability index 0.071587 pu and emission levels 0.09055 ton/h. Figure 8 displays the convergence curves of the CHIO, the ALO, and the SSA techniques over several test schemes. These records illustrate that the CHIO influences the best values of the OF in the least number of iterations, consistently: for all test scenarios (1–5), the CHIO reaches the lowest OFs in comparison with the other methods in a smaller number of iterations, which proves the effectiveness of the presented technique.

![Figure 8. Cont.](image-url)
Figure 8. Convergence rates for Scenarios 1, 2, 3, 4, and 5 with CHIO, ALO, and SSA: (a) convergence rates for Scenario 1; (b) convergence rates for Scenario 2; (c) convergence rates for Scenario 3; (d) convergence rates for Scenario 4; (e) convergence rates for Scenario 5.

The proposed CHIO compared with the reported methods for Scenarios 1–5 is given in Table 9. In comparison to the literature approaches, the proposed CHIO contributes to competitiveness strategy for different scenarios (1–5).

Table 9. Comparative analysis for SO functions for IEEE 30-bus test scheme (Scenarios 1–5) (The numbers in bold are the best values found).

| Scenarios | Scenario #1 | Scenario #2 | Scenario #3 | Scenario #4 | Scenario #5 |
|-----------|-------------|-------------|-------------|-------------|-------------|
| IGWO [52] | 811.838     | 0.09783     | -           | 2.3584      | -           |
| DA-PSO [37]| 802.12      | 0.205       | -           | 3.189       | -           |
| MOALO [70]| 799.14      | -           | -           | -           | -           |
| MODA [71]| 802.32      | -           | -           | -           | -           |
| WOA-PS [71]| 799.56     | 0.206       | -           | 2.967       | -           |
| PSO-SSO [72]| 798.98    | 0.205       | 1.25        | 2.858       | 0.124       |
| ECBO [73]| 799.035     | -           | -           | -           | -           |
| ECHT [36]| 800.41      | 0.205       | -           | 3.084       | 0.136       |
| DA-APSO [74]| 802.63    | -           | -           | 3.003       | -           |
| MVO [75]| 799.24      | -           | -           | 2.881       | 0.115       |
| ALO | 769.32      | 0.090553    | 0.37794     | 2.0724      | 0.071614    |
| SSA  | 769.64      | 0.090553    | 0.37173     | 2.0848      | 0.071596    |
| CHIO | 768.95      | 0.090550    | 0.36824     | 2.0661      | 0.071587    |

5.1.2. Dual-Objective Scenarios

Tables 10 and 11 represent the scheduling of control variables and the simulation results of dual-objective scenarios (Scenarios 6–8) using the AHP, respectively. Scenario 6 enhances the fuel and emissions of generation stations concurrently. Scenario 7 enhances fuel costs and $VD$, while Scenario 8 reflects the fuel costs and the stability enhancement as the main dual-objective. The presented CHIO indicates the best compromise alternatives for Scenarios 6–8. The findings obtained the success of the presented CHIO compared to the literary methods mentioned. Figure 9 shows the efficacy of the CHIO technique proposed as opposed to the other algorithms SSA and ALO using the AHP technique.
### Table 10. Lists of control variables for Scenarios 6–8 for IEEE 30-bus test scheme: AHP-based solutions (The numbers in bold are the best values found).

| Variables and Parameters | Bounds | Scenario #6 | Scenario #7 | Scenario #8 |
|--------------------------|--------|-------------|-------------|-------------|
|                          | Min    | Max         | CHIO        | ALO         | SSA         | CHIO        | ALO         | SSA         |
| Active power (MW)        | 10     | 60          | 38,259      | 38,366      | 38,253      | 38,639      | 39,291      | 38,74       | 38,683      | 38,721      | 39,174      |
| PTPG2                   | 20     | 80          |             |             |             |             |             |             |             |             |             |
| PTPG5                   | 43,679 | 42,398      |             |             |             |             |             |             |             |             |             |
| PTPG8                   | 32,958 | 31,971      | 32,57       | 32,446      | 31,722      | 31,403      | 31,862      | 32,205      | 33,668      |             |             |
| PTPG11                  | 10     | 60          |             |             |             |             |             |             |             |             |             |
| Reactive power (MVAr)   | −20    | 60          | 10,833      | 10,874      | 9,6167      | 11,811      | 11,203      | 11,390      | 11,203      | 11,390      | 11,203      |
| Q2                      | −30    | 35          |             |             |             |             |             |             |             |             |             |
| Q5                      | −15    | 40          |             |             |             |             |             |             |             |             |             |
| Q8                      | −25    | 30          | 19,086      | 18,154      | 18,192      | 19,127      | 18,950      | 18,321      | 18,226      | 18,950      | 18,321      |
| Bus voltage (pu)        | 0.96   | 1.10        | 1.0899      | 1.0905      | 1.0897      | 1.0879      | 1.0895      | 1.0901      | 1.0901      | 1.0895      | 1.0901      |
| V1                      | 1.10   |             |             |             |             |             |             |             |             |             |             |
| V2                      | 1.10   |             |             |             |             |             |             |             |             |             |             |
| V3                      | 1.10   |             |             |             |             |             |             |             |             |             |             |
| W gen cost              | Not applicable |           |             |             |             |             |             |             |             |             |             |
| PV gen cost             | 114.16 | 117.71      | 114.14      | 115.37      | 117.47      | 115.7       | 115.51      | 115.63      | 115.09      | 115.51      | 115.63      |
| PVTPEnergy              | 99.824 | 98.776      | 98.611      | 98.248      | 96.042      | 95.024      | 96.568      | 97.476      | 102.11      | 96.568      | 97.476      |
| Fuel costs ($/h)        | 436.16 | 439.69      | 452.51      | 445.08      | 440.45      | 441.12      | 446.73      | 454.86      | 452.84      | 446.73      | 454.86      |
| VD (pu)                 | 0.96   | 1.10        | 1.0999      | 1.0769      | 1.0874      | 1.0886      | 1.0919      | 1.0975      | 1.0901      | 1.0919      | 1.0975      |
| V13                     | 1.10   |             |             |             |             |             |             |             |             |             |             |
| V13                      | 1.10   |             |             |             |             |             |             |             |             |             |             |
| Emissions (ton/h)        | 0.1478 | 0.1506      | 0.15161     | 0.15101     | 0.15036     | 0.14771     | 0.15158     | 0.15475     | 0.15446     | 0.15158     | 0.15475     |
| Execution time (s)      | 385.0354 | 353.1225 | 384.7674 | 343.9965 | 348.5127 | 430.5964 | 309.6968 | 408.3730 | 391.4546 |             |             |

**Figure 9.** Convergence rates for Scenarios 6, 7, and 8 with CHIO, ALO, and SSA: (a) convergence rates for Scenario #6; (b) convergence rates for Scenario 7; (c) convergence rates for Scenario 8.
Table 11. Numerical results of Scenarios 6–8 for IEEE 30-bus test scheme “Dual-objectives”.

| Scenarios | Scenario #6 | Scenario #7 | Scenario #8 |
|-----------|-------------|-------------|-------------|
| Optimizations | CHIO | ALO | SSA | CHIO | ALO | SSA | CHIO | ALO | SSA |
| Fuel costs ($/h) | 769.79 | 769.91 | 770.19 | 768.89 | 769.60 | 770.50 | 769.49 | 769.55 | 770.22 |
| Emissions (ton/h) | 0.1478 | 0.1501 | 0.1516 | 0.1510 | 0.1504 | 0.1477 | 0.1516 | 0.1548 | 0.1545 |
| VD (pu) | 1.0767 | 1.1414 | 1.1208 | 0.8739 | 0.9668 | 0.8801 | 1.0753 | 1.1121 | 1.0101 |
| $P_{\text{loss}}$ (MW) | 5.3788 | 5.4231 | 5.5705 | 5.4964 | 5.4315 | 5.5104 | 5.5244 | 5.6632 | 5.6270 |
| $L$-index | 0.1139 | 0.1115 | 0.1123 | 0.1223 | 0.1179 | 0.1241 | 0.1139 | 0.1126 | 0.1169 |

Figure 10 explains the Pareto fronts with the strategies CHIO, ALO, and SSA for Scenarios 6–8. In Scenarios 6–8, Table 12 demonstrates the numerical results of the presented CHIO using TOPSIS in comparison with further utilized techniques. The use of the CHIO is more competitive in various scenarios relative to the approaches described.

Figure 10. Pareto fronts with CHIO, ALO, and SSA for Scenario 6–8. (a) Pareto fronts with CHIO, ALO, and SSA for Scenario 6; (b) Pareto fronts with CHIO, ALO, and SSA for Scenario 7; (c) Pareto fronts with CHIO, ALO, and SSA for Scenario 8.
### Table 12. Lists of control variables for Scenarios 6–8 for IEEE 30-bus test scheme: TOPSIS-based solutions (The numbers in bold are the best values found).

| Variables and Parameters | Scenario #6 | Scenario #7 | Scenario #8 |
|--------------------------|-------------|-------------|-------------|
|                         | Min  | CHIO | ALO | SSA | Min  | CHIO | ALO | SSA | Min  | CHIO | ALO | SSA |
| Active power (MW) PTPG 2 | 80   | 47.845 | 48.982 | 46.078 | 45.621 | 40.152 | 66.178 | 39.117 | 47.489 | 42.04 |
| Active power (MW) PTPG 5 | 60   | 49.719 | 53.164 | 51.233 | 24.064 | 55.8 | 40.281 | 42.978 | 42.409 | 45.261 |
| Active power (MW) PTPG 8 | 35   | 33.338 | 29.341 | 30.902 | 22.187 | 31.809 | 26.5 | 30.152 | 33.634 | 31.53 |
| Reactive power (MVAr) Q 2 | −20  | 12.779 | −19.618 | 12.779 | −20 | −20 | −20 | −20 | −17.095 | −20 |
| Reactive power (MVAr) Q 5 | −30  | 34.737 | 34.737 | 34.737 | 34.737 | 34.737 | 34.737 | 34.737 | 34.737 | 34.737 |
| Reactive power (MVAr) Q 8 | −15  | 40    | 40    | 40    | 40    | 40    | 40    | 40    | 40    |
| Reactive power (MVAr) Q 11| −25  | 20.212 | 20.212 | 20.212 | 20.212 | 20.212 | 20.212 | 20.212 | 20.212 |
| Reactive power (MVAr) Q 13| −20  | 30    | 30    | 30    | 30    |

### Table 13. Comparative analysis for dual objective functions (Scenarios 6–8).

| Scenarios | Objective Functions | Scenario #6 | Scenario #7 | Scenario #8 |
|-----------|---------------------|-------------|-------------|-------------|
|           | Fuel Costs ($/h)    | Emissions (ton/h) | Fuel Costs ($/h) | VD (pu) | Fuel Costs ($/h) | L-Index |
| MOMICA [34]| 865.06             | 0.222       | 804.96   | 0.095      | -     | -            |
| MOFA-CPA [33]| 852.02           | 0.279       | -         | -         | -     | -            |
| MODA [37]| 838.604            | 0.254       | 807.2807 | 0.023      | -     | -            |
| PSO-SSO [72]| 834.804          | 0.243       | 803.99   | 0.094      | 830.35 | 0.125        |
| ECHT [36]| -                  | -           | 803.72   | 0.113     | -     | -            |
| DA-APSO [74]| -                | -           | 802.63   | 0.116      | -     | -            |
| ALO        | 769.91             | 0.15006     | 769.6    | 0.96677    | 769.55 | 0.11388     |
| SSA       | 770.19             | 0.15161     | 770.5    | 0.88008    | 770.22 | 0.11259     |
| CHIO      | 769.79             | 0.1478      | 768.89   | 0.87394    | 769.49 | 0.11691     |

An evaluation of the previous related studies for dual objectives was stated in Table 13. The results obtained the effectiveness of the presented CHIO compared to the literary methods mentioned. The results in bold are more competitive solutions using three optimization techniques.

### Table 13. Comparative analysis for dual objective functions (Scenarios 6–8).

5.1.3. Triple-Objective Scenarios

Tables 14 and 15 display the outcomes of simulations obtained for three objective functions for the SSA, the ALO, and the proposed CHIO for Scenarios 9–11 using the AHP and the TOPSIS, respectively. In Scenario 9, three objectives are taken into account: fuel costs, power losses, and voltage deviation minimizations. In Scenario 10, fuel cost, $P_{loss}$, and carbon minimizations are considered. The fuel costs, voltage drop, and emission levels are considered in Scenario 11.
Table 14. Lists of control variables for Scenarios 9–11 for IEEE 30-bus test scheme: AHP-based solutions (The numbers in bold are the best values found).

| Variables and Parameters | Bounds | Scenario #9 | Scenario #10 | Scenario #11 |
|-------------------------|--------|-------------|-------------|-------------|
|                        | Min    | Max         | CHIO        | ALO         | SSA         |
| Active power (MW)       | 0      | 80          | 37.915      | 37.263      | 37.519      | 37.575      | 37.915      | 36.998      | 36.901      | 37.704      | 38.33       |
| Reactive power (MVAR)   | 0      | 60          | 37.924      | 38.554      | 42.819      | 41.433      | 41.144      | 42.807      | 43.679      | 37.467      | 39.543      |
| Bus voltage (pu)        | 0.96   | 1.10        | 0.49861     | 0.49895     | 0.49915     | 0.49961     | 0.49961     | 0.49957     | 0.49951     | 0.49946     | 0.49939     |
| Emissions (ton/h)       | 0.09112 | 0.09411   | 0.09662     | 0.09682     | 0.09702     | 0.09722     | 0.09722     | 0.09742     | 0.09752     | 0.09762     | 0.09786     |
| Execution time (s)      | 279.63 | 347.842     | 362.581     | 274.884     | 375.193     | 384.989     | 272.287     | 364.287     | 385.129     |             |             |

Table 15. Lists of control variables for Scenarios 9–11 for IEEE 30-bus test scheme: TOPSIS-based solutions (The numbers in bold are the best values found).

| Variables and Parameters | Bounds | Scenario #9 | Scenario #10 | Scenario #11 |
|-------------------------|--------|-------------|-------------|-------------|
|                        | Min    | Max         | CHIO        | ALO         | SSA         |
| Active power (MW)       | 0      | 80          | 45.405      | 48.361      | 62.321      | 46.448      | 53.022      | 45.228      | 57.368      | 48.538      | 49.279      |
| Reactive power (MVAR)   | 0      | 60          | 50.529      | 50.909      | 52.175      | 71.7        | 56.496      | 54.824      | 49.2        | 46.063      | 48.875      |
| Bus voltage (pu)        | 0.96   | 1.10        | 1.18490     | 1.18512     | 1.18230     | 1.18335     | 1.18335     | 1.18365     | 1.18490     | 1.18512     | 1.18230     |
| Emissions (ton/h)       | 0.09112 | 0.09411   | 0.09662     | 0.09682     | 0.09702     | 0.09722     | 0.09722     | 0.09742     | 0.09752     | 0.09762     | 0.09786     |
| Execution time (s)      | 279.63 | 347.842     | 362.581     | 274.884     | 375.193     | 384.989     | 272.287     | 364.287     | 385.129     |             |             |

In Scenario 9, the proposed CHIO obtained the best fuel cost and voltage deviation, while the SSA technique achieved the best reduction in power losses. In Scenario 10, the proposed CHIO obtained the best economic benefit, while the SSA technique obtained the best reduction in power losses and environmental benefits. In Scenario 11, the proposed CHIO obtained the best values in all objectives of that scenario. Figure 11 indicates Pareto fronts with ALO, SSA, and the proposed CHIO methods for Scenarios 9–11.
The fuel costs in Scenarios 9, 10, and 11 obtained using the AHP are more economical than obtained using a TOPSIS. In Scenario 9, voltage deviation and power losses obtained using a TOPSIS are more technical than obtained using the AHP. In Scenario 10, emission levels and power losses obtained using a TOPSIS are more environmental and technical than obtained using the AHP, respectively. In addition, voltage deviation and emission levels obtained in Scenario 11 using a TOPSIS are more technical and offer more environ-
mental benefits than obtained using the AHP, respectively. To sum up, we can say that optimization techniques using the AHP are superior to obtaining the best values of fuel costs in comparison to the TOPSIS while the optimization techniques using the TOPSIS has more environmental and technical benefits in comparison to the AHP in the case of triple-objective scenarios. An evaluation of the previous related studies for triple-objectives is stated in Table 16. The results obtained the effectiveness of the presented CHIO in comparison with the literary methods mentioned. The results in bold are more competitive solutions using three optimization techniques.

Table 16. Comparative analysis for triple-objective functions (Scenarios 9–11) (The numbers in bold are the best values found).

| Scenarios | Scenario #9 | Scenario #10 | Scenario #11 |
|-----------|-------------|--------------|--------------|
| Objective Functions | Fuel Costs ($/h) | VD (pu) | Power Losses (MW) | Fuel Costs ($/h) | Emissions (ton/h) | Power Losses (MW) | Fuel Costs ($/h) | Emissions (ton/h) | VD (pu) |
| MOFA-CPA [33] | - | - | - | 878.13 | 0.2165 | 3.9232 | - | - | - |
| MODA [37] | - | - | - | 867.9070 | 0.2640 | 4.5342 | - | - | - |
| PSO-SSO [72] | 864.27 | 0.316 | 4.545 | 865.18 | 0.224 | 4.093 | 804.332 | 0.346 | 0.164 |
| ALO | 769.19 | 0.96724 | 5.547 | 770.3 | 0.14763 | 5.367 | 769.97 | 0.15521 | 0.88963 |
| SSA | 769.91 | 0.95242 | 5.3219 | 769.56 | 0.14732 | 5.3112 | 769.85 | 0.14897 | 0.78891 |
| CHIO | 769.53 | 0.89865 | 5.5598 | 769.38 | 0.14855 | 5.3811 | 769.85 | 0.14897 | 0.78891 |

5.1.4. Quad-Objective Scenario

Table 17 displays EETD simulation results for the quad objective “Scenario 12”. This table confirms that the presented CHIO leads, in comparison with the ALO and the SSA using the TOPSIS, to the most competitive economic solutions at tolerable voltages of system losses. The convergence curve in Figure 12 displays the efficiency and the minimum number of iterations of the proposed CHIO method using the AHP. Furthermore, Table 18 assesses the CHIO offered as compared to MOMICA [34], I-NSGA-III [35], MODA [37], and ECHT [36] in the context of Scenario 12 and individual ALO and SSA techniques. In comparison to existing individual optimization methods using the ALO and the SSA, the proposed CHIO approach offers the best possible compromise solution.

Table 17. Lists of control variables for Scenario 12 for IEEE 30-bus test scheme: TOPSIS-based solutions (The numbers in bold are the best values found).

| Variables and Parameters | Min. | Max. | CHIO | ALO | SSA |
|--------------------------|------|------|------|-----|-----|
| Active power (MW) | | | | | |
| \( P_{TG2} \) | 20 | 80 | 48.714 | 50.953 | 47.125 |
| \( P_{TG5} \) | 10 | 60 | 48.81 | 54.609 | 50.637 |
| \( P_{TG8} \) | 10 | 35 | 27.752 | 33.426 | 31.178 |
| \( P_{TG11} \) | 10 | 60 | 54.453 | 48.113 | 54.953 |
| \( P_{TG13} \) | 10 | 48.652 | 39.445 | 36.464 | 43.843 |
| Reactive power (MVAr) | | | | | |
| \( Q_2 \) | -20 | 60 | 33.559 | 6.7174 | -20 |
| \( Q_5 \) | -30 | 35 | 26.541 | 35 | 28.401 |
| \( Q_8 \) | -15 | 40 | 40 | 38.79 | 40 |
| \( Q_{11} \) | -25 | 30 | 16.525 | 17.953 | 16.23 |
| \( Q_{13} \) | -20 | 25 | 14.031 | 14.739 | 12.23 |
| Bus voltage (pu) | | | | | |
| \( V_1 \) | 0.96 | 1.10 | 1.071 | 1.0769 | 1.0804 |
| \( V_2 \) | 0.96 | 1.10 | 1.0723 | 1.0716 | 0.99356 |
| \( V_5 \) | 0.96 | 1.10 | 1.0543 | 1.074 | 1.0452 |
| \( V_8 \) | 0.96 | 1.10 | 1.0697 | 1.0619 | 1.05 |
| \( V_{11} \) | 0.96 | 1.10 | 1.0634 | 1.0759 | 1.0526 |
| \( V_{13} \) | 0.96 | 1.10 | 1.0499 | 1.0581 | 1.0363 |


Table 17. Cont.

| Variables and Parameters | Min. | Max. | CHIO    | ALO     | SSA     |
|--------------------------|------|------|---------|---------|---------|
| \( W_{\text{gencost}} \) | 150.62 | 172.84 | 157.47 |
| \( P_{\text{gencost}} \) | 159.28 | 172.84 | 160.63 |
| \( P_{\text{PVTP}} \) | 121.73 | 117.72 | 138.18 |
| \( \text{Fuel}_{\text{gencost}} \) | 375.46 | 392.93 | 361.45 |
| \( V_{\text{D}} \) (pu) | Not applicable | | | |
| \( P_{\text{loss}} \) (MW) | 3.2669 | 2.9596 | 3.1828 |
| \( L\text{-index} \) | 0.11517 | 0.11298 | 0.13688 |
| \( \text{Emission (ton/h)} \) | 0.095747 | 0.093889 | 0.092843 |
| \( \text{Computation time (s)} \) | 1070.1630 | 302.5195 | 404.1681 |

Figure 12. Convergence rates for Scenario 12 with ALO, SSA, and CHIO.

Table 18. Lists of control variables for Scenario 13 for IEEE 30-bus test scheme: TOPSIS-based solutions (The numbers in bold are the best values found).

| Variables and Parameters | Min. | Max. | CHIO    | ALO     | SSA     |
|--------------------------|------|------|---------|---------|---------|
| Active power (MW)        |      |      |         |         |         |
| \( P_{\text{TG2}} \)     | 20   | 80   | 73.507  | 47.479  | 47.016  |
| \( P_{\text{TG5}} \)     | 10   | 60   | 54.844  | 45.5    | 47.761  |
| \( P_{\text{TG8}} \)     | 10   | 35   | 33.146  | 25.043  | 33.585  |
| \( P_{\text{TG11}} \)    | 10   | 60   | 56.072  | 46.144  | 46.941  |
| \( P_{\text{TG13}} \)    | 10   | 48.652 | 38.813  | 35.025  | 40.565  |
| Reactive power (MVAr)    |      |      |         |         |         |
| \( Q_2 \)                | –20  | 60   | –20     | 1.6023  | 33.452  |
| \( Q_5 \)                | –30  | 35   | 35      | 31.742  | 6.0559  |
| \( Q_8 \)                | –15  | 40   | 40      | 40      | 40      |
| \( Q_{11} \)             | –25  | 30   | 37.94   | 20.115  | 24.597  |
| \( Q_{13} \)             | –20  | 25   | 44.923  | 25      | 25      |
| Bus voltage (pu)         |      |      |         |         |         |
| \( V_1 \)                | 0.96 | 1.10 | 1.0326  | 1.0659  | 1.0516  |
| \( V_2 \)                | 0.96 | 1.10 | 0.97156 | 1.0572  | 1.0502  |
| \( V_5 \)                | 0.96 | 1.10 | 1.0951  | 1.0475  | 1.0134  |
| \( V_9 \)                | 0.96 | 1.10 | 1.0909  | 1.0718  | 1.0592  |
| \( V_{11} \)             | 0.96 | 1.10 | 1.0948  | 1.0763  | 1.0775  |
| \( V_{13} \)             | 0.96 | 1.10 | 1.0941  | 1.0916  | 1.0695  |
| \( W_{\text{gencost}} \) | 173.76 | 138.58 | 146.75 |
| \( P_{\text{gencost}} \) | 164.98 | 128.43 | 131.24 |
| \( P_{\text{gencost}} \) | 119.51 | 106.59 | 125.99 |
| \( \text{Fuel}_{\text{gencost}} \) | 406 | 414.66 | 400.5 |
| \( V_{\text{D}} \) (pu) | Not applicable | | | |
| \( P_{\text{loss}} \) (MW) | 0.39559 | 0.35259 | 0.42219 |
| \( L\text{-index} \) | 0.075979 | 0.11077 | 0.10948 |
| \( \text{Emission (ton/h)} \) | 0.096721 | 0.10653 | 0.096649 |
| \( \text{Computation time (s)} \) | 991.7640 | 347.8191 | 358.4133 |
5.1.5. Quanta-Objective Scenario

Table 18 demonstrates the results of the EETD issue for quanta-objectives “Scenario 13”. The table confirms that the presented CHIO indicates more competitive compromise alternatives at appropriate thresholds of voltage at the losses to the system in comparison with the ALO and the SSA. It can be noted from Figure 13 that the presented CHIO attains the best alternative. Furthermore, Table 19 assesses the CHIO offered as compared to MOMICA [34], I-NSGA-III [35], MODA [37], and ECHT [36] in the context of Scenario 13.

![Figure 13. Convergence rates for Scenario 13 with ALO, SSA, and CHIO.](image)

Table 19. Comparative analysis for quad and quanta objective functions (Scenarios 12 and 13) (The numbers in bold are the best values found).

| Scenarios | Scenario #12 | Scenario #13 |
|-----------|--------------|--------------|
| Objective Functions | Fuel Costs ($/h) | Emission (ton/h) | VD (pu) | Power Losses (MW) | Fuel Costs ($/h) | Emissions (ton/h) | VD (pu) | Power Losses (MW) | L-Index |
| MOMICA [34] | 830.188 | 0.252 | 0.298 | 5.585 | - | - | - | - | - |
| I-NSGA-III [35] | 881.9395 | 0.2209 | 0.1754 | 4.7449 | 843.8571 | 0.1485 | 0.2388 | 5.7405 | 0.1253 |
| MODA [37] | 828.49 | 0.265 | 0.585 | 5.912 | - | - | - | - | - |
| ECHT [36] | 830.2123 | 0.253 | 0.296 | 5.586 | - | - | - | - | - |
| PSO-SSO [72] | 826.94 | 0.258 | 0.466 | 5.515 | 826.8 | 0.256 | 0.463 | 5.464 | 0.145 |
| ALO | 769.07 | 0.14957 | 0.84792 | 5.5493 | 769.93 | 0.14867 | 0.97541 | 5.3714 | 0.11758 |
| SSA | 770.43 | 0.14799 | 0.83337 | 5.4257 | 770.18 | 0.15455 | 0.8247 | 5.6446 | 0.12473 |
| CHIO | 768.92 | 0.15177 | 0.92664 | 5.4395 | 770.13 | 0.14624 | 0.86862 | 5.3023 | 0.12242 |

5.2. Results for IEEE 57-Bus Scheme

For SO and MO scenarios for the second test scheme, the simulation findings are stated as follows:

5.2.1. Single Objective Scenarios

For the IEEE-57 bus scheme, Table 20 shows the SOEETD alternatives obtained by the ALO, the SSA, and the presented CHIO for Scenario 14. In this scenario, the minimization of fuel costs is the main OF. The presented CHIO tends to be the least economical alternative (USD 32,752/h) in comparison with other approaches the ALO (USD 32,756/h) and the SSA (USD 32,770/h). Figure 14 illustrates the convergence rates of the proposed CHIO in comparison to other algorithms of the ALO and the SSA. This figure shows that the CHIO attains the best estimates of the OF in the least number of iterations.
Table 20. Lists of control variables for Scenario 14 for IEEE 57-bus test scheme (The numbers in bold are the best values found).

| Variables and Parameters | Bounds | Scenario #14 |
|--------------------------|--------|--------------|
|                          | Min    | Max          | CHIO | ALO | SSA |
| Active power (MW)        |        |              |      |     |     |
| $P_{TPC1}$               | 80     | 200          | 142.03 | 143.32 | 142.02 |
| $P_{TPC2}$               | 30     | 100          | 100   | 100  | 100  |
| $P_{TPC3}$               | 40     | 140          | 140   | 140  | 140  |
| $P_{TPC6}$               | 30     | 100          | 90.462 | 99.915 | 85.404 |
| $P_{TPG8}$               | 100    | 550          | 381.24 | 375.31 | 384.08 |
| $P_{TPG9}$               | 30     | 100          | 48.64 | 48.587 | 48.605 |
| $P_{TPG12}$              | 100    | 410          | 362.39 | 362.87 | 364.11 |

| Reactive power (MVar)    |        |              |      |     |     |
| $Q_2$                    | -17    | 50           | 46.138 | 49.685 | 50  |
| $Q_3$                    | -10    | 60           | 29.639 | 28.616 | -10 |
| $Q_6$                    | -8     | 25           | 5.0015 | 1.2401 | -8  |
| $Q_8$                    | -140   | 200          | 42.065 | 40.539 | 69.403 |
| $Q_9$                    | -3     | 9            | 5     | 9    | -3  |
| $Q_{12}$                 | -150   | 155          | 56.541 | 67.292 | 69.611 |

| Bus voltage (pu)         |        |              |      |     |     |
| $V_1$                    | 0.95   | 1.10         | 1.1  | 1.0991 | 1.1 |
| $V_2$                    | 0.95   | 1.10         | 1.1  | 1.1  | 1.0999 |
| $V_3$                    | 0.95   | 1.10         | 1.1  | 1.1  | 1.0078 |
| $V_6$                    | 0.95   | 1.10         | 1.1  | 1.1  | 1.0994 |
| $V_9$                    | 0.95   | 1.10         | 1.1  | 1.1  | 0.9591 |
| $V_{11}$                 | 0.95   | 1.10         | 1.1  | 1.1  | 1.1 |
| $V_{12}$                 | 0.95   | 1.10         | 1.1  | 1.098 | 1.0423 |
| $W_{gencost}$            |        |              | 555.43 | 555.43 | 555.43 |
| $PV_{gencost}$           |        |              | 1646.6 | 1616.9 | 1658.4 |
| $PVT_{gencost}$          |        |              | 156.77 | 156.37 | 156.63 |
| $Fuel_{vlvcost}$         |        |              | 30.393 | 30.427 | 30.399 |
| Fuel costs ($/h)         |        |              | 32,752 | 32,756 | 32,770 |
| $V_D$ (pu)               |        |              | 4.9146 | 4.9821 | 4.5556 |
| $P_{loss}$ (MW)          |        |              | 12.738 | 12.708 | 13.098 |
| $L_{-index}$             |        |              | 0.2321 | 0.2294 | 0.2417 |
| Emissions (ton/h)        |        |              | 1.2322 | 1.2582 | 1.2763 |
| Computation time (s)     |        |              | 347.42 | 399.24 | 609.65 |

Figure 14. Convergence rates for Scenario 14 with ALO, SSA, and CHIO.
5.2.2. Dual-Objective Scenarios “Economical and Technical Benefits”

In Scenario 15, the fuel costs and $VD$ can be enhanced concurrently. The presented CHIO tends to the optimal compromise alternative using the AHP (USD 32,754/h) and (4.8974 pu) in comparison with other individual approaches; the ALO (USD 32,771/h) and (4.9926 pu); and the SSA (USD 32,786/h) and (4.6149 pu). The proposed CHIO leads to the optimal compromise solution using the TOPSIS (USD 33,299/h) and (1.0707 pu) in comparison with other individual techniques; the ALO (USD 32,935/h) and (1.0937 pu); and the SSA (USD 33,230/h) and (1.0872 pu); as illustrated in Table 21. The fuel cost using the CHIO-AHP and voltage deviation using the SSA-AHP are more economical and technical than obtained using other approaches, respectively.

Table 21. Lists of control variables for Scenario 15 using AHP and TOPSIS for IEEE 57-bus test scheme (The numbers in bold are the best values found).

| Variables and Parameters | Bounds | Scenario #15—AHP | Scenario #15—TOPSIS |
|--------------------------|--------|------------------|---------------------|
|                          | Min    | Max              | CHIO ALO SSA        | CHIO ALO SSA        |
| Active power (MW)        |        |                  |                     |                     |
| $P_{TPG1}$               | 80     | 200              | 141.13              | 146.85              | 142.12              |
| $P_{TPG2}$               | 30     | 100              | 100                 | 100                 | 100                 |
| $P_{TPG3}$               | 40     | 140              | 140                 | 140                 | 140                 |
| $P_{TPG6}$               | 30     | 100              | 90.525              | 66.72               | 64.232              |
| $P_{TPG8}$               | 100    | 550              | 381.28              | 391.52              | 390.9               |
| $P_{TPG9}$               | 30     | 100              | 48.555              | 48.524              | 48.595              |
| $P_{TPG12}$              | 100    | 410              | 362.39              | 374                 | 375.88              |
| Reactive power (MVAr)    |        |                  |                     |                     |
| $Q_2$                    | −17    | 50               | 50                  | 47.376              | 50                 |
| $Q_3$                    | −10    | 60               | 30.456              | 28.034              | −10                |
| $Q_6$                    | −8     | 25               | 5.0223              | 9.0762              | −8                 |
| $Q_8$                    | −140   | 200              | 42.625              | 37.959              | 63.327              |
| $Q_9$                    | −3     | 9                | 9                   | 9                   | 9                  |
| $Q_{12}$                 | −150   | 155              | 56.269              | 63.386              | 65.015              |
| Bus voltage (pu)         |        |                  |                     |                     |
| $V_1$                    | 0.95   | 1.10             | 1.099               | 1.0996              | 1.1                |
| $V_2$                    | 0.95   | 1.10             | 1.1                 | 1.1                 | 1.0977             |
| $V_3$                    | 0.95   | 1.10             | 1.1                 | 1.1                 | 0.9876             |
| $V_6$                    | 0.95   | 1.10             | 1.1                 | 1.1                 | 1.0437             |
| $V_8$                    | 0.95   | 1.10             | 1.1                 | 1.1                 | 1.1                |
| $V_{11}$                 | 0.95   | 1.10             | 1.1                 | 1.1                 | 1.1                |
| $V_{12}$                 | 0.95   | 1.10             | 1.0815              | 1.0866              | 1.0836             |
| $W_{gen\text{cost}}$     | 555.43 | 555.43           | 555.43              | 539.82              | 555.32              |
| $PV_{gen\text{cost}}$    | 1645.4 | 1691.9           | 1689.8              | 1706.3              | 1732.7              |
| $PVTT_{gen\text{cost}}$  | 156.45 | 156.33           | 156.6               | 152.24              | 156.33              |
| $Fuel_{v\text{lv\text{cost}}}$ | 30.397 | 30.367           | 30.384              | 30.900              | 30.490              |
| Fuel costs ($/h)         | Not applicable | 32,754           | 32,771              | 32,786              | 32,929              |
| $VD$ (pu)                | 4.8974 | 4.9926           | 4.6149              | 4.1070              | 4.0937              |
| $P_{\text{loss}}$ (MW)   | 12.736 | 12.458           | 12.717              | 16.833              | 16.794              |
| $L$-index                | 0.23147 | 0.22979         | 0.2404             | 0.26182             | 0.26843             |
| Emissions (ton/h)        | 1.2584 | 1.341            | 1.3454              | 1.3261              | 1.3465              |
| Computation time (s)     | 427.485 | 414.692 | 596.62             | 1303.38             | 455.579             |

The fuel cost using the ALO-TOPSIS and voltage deviation using the CHIO-TOPSIS are more economical and technical than obtained using other approaches, respectively. Figure 15 shows the convergence rate and the Pareto front for the dual objectives for Scenario 15 using the AHP and the TOPSIS, respectively.

5.2.3. Dual-Objective Scenarios “Economical and Environmental Benefits”

In Scenario 16, the fuel costs and emissions are concurrently enhanced. The presented CHIO tends to be the optimal compromise alternative using the AHP (USD 32,751/h) and (1.2553 ton/h) in comparison with other approaches; the ALO (USD 32,753/h) and...
(1.2581 ton/h); and the SSA (USD 32,772/h) and (1.3422 ton/h). The proposed CHIO leads to the optimal compromise alternative using the TOPSIS (USD 33,344/h) and (1.0976 ton/h) compared with other approaches; the ALO (USD 33,049/h) and (1.1198 ton/h); and the SSA (USD 33,473/h) and (1.0964 ton/h) as illustrated in Table 22. The fuel cost and emission levels obtained using the CHIO-AHP are more economical and environmental than obtained using other approaches, respectively.

![Figure 15. The convergence rate and the Pareto front for the dual-objective for Scenario 15 using the AHP and TOPSIS: (a) convergence rates using the AHP with ALO, SSA, and CHIO; (b) Pareto fronts with CHIO, ALO, and SSA.](image)

**Table 22.** Lists of control variables for Scenario 16 using AHP and TOPSIS for IEEE 57-bus test scheme

(The numbers in bold are the best values found.)

| Variables and Parameters | Bounds | Scenario #16—AHP | Scenario #16—TOPSIS |
|--------------------------|--------|-----------------|---------------------|
|                          | Min    | Max             | CHIO                | ALO          | SSA     | CHIO                | ALO          | SSA     |
| Active power (MW)        |        |                 |                     |              |         |                     |              |         |
| $P_{TPG1}$               | 80     | 200             | 140.44              | 142.84       | 158.66  | 140.44              | 142.84       | 158.66  |
| $P_{TPG2}$               | 30     | 100             | 100                 | 100          | 100     | 100                 | 100          | 100     |
| $P_{TPG3}$               | 40     | 140             | 140                 | 140          | 140     | 139.99              | 140          | 139.99  |
| $P_{TPG6}$               | 30     | 100             | 90.488              | 95.416       | 65.626  | 99.938              | 100          | 99.78   |
| $P_{TPG8}$               | 100    | 550             | 381.21              | 384.31       | 392.53  | 320.04              | 336.72       | 320.58  |
| $P_{TPG9}$               | 30     | 100             | 48.653              | 48.614       | 48.601  | 48.59              | 48.70        | 48.58   |
| $P_{TPG12}$              | 100    | 410             | 362.38              | 357.39       | 372.12  | 339.96              | 345.59       | 334.15  |
| Reactive power (MVar)    |        |                 |                     |              |         |                     |              |         |
| $Q_2$                    | −17    | 50              | 46.138              | 49.066       | 49.93   | 45.377              | 45.545       | 30.186  |
| $Q_3$                    | −10    | 60              | 29.64               | 28.429       | 30.756  | 26.853              | 21.835       | 4.2581  |
| $Q_6$                    | −8     | 25              | 4.9955              | 3.4006       | 10.004  | 7.0424              | 4.1125       | 8       |
| $Q_8$                    | −140   | 200             | 42.068              | 39.15        | 47.067  | 44.505              | 35.441       | 83.674  |
| $Q_9$                    | −3     | 9               | 9                   | 9            | −3      | 9                   | 9            | 9       |
| $Q_{12}$                 | −150   | 155             | 56.541              | 67.055       | 61.353  | 80.818              | 102.34       | 48.528  |
| Bus voltage (pu)         |        |                 |                     |              |         |                     |              |         |
| $V_1$                    | 0.95   | 1.10            | 1.1                 | 1.0993       | 1.099   | 1.0995              | 1.1          | 1.0934  |
| $V_2$                    | 0.95   | 1.10            | 1.1                 | 1.1          | 1.1     | 1.0994              | 1.1          | 1.0852  |
| $V_3$                    | 0.95   | 1.10            | 1.1                 | 1.1          | 1.1     | 1.0992              | 1.1          | 1.0724  |
| $V_6$                    | 0.95   | 1.10            | 1.1                 | 1.1          | 1.1     | 1.0992              | 1.1          | 1.0456  |
| $V_8$                    | 0.95   | 1.10            | 1.1                 | 1.1          | 1.1     | 1.0987              | 1.1          | 1.0915  |
| $V_{11}$                 | 0.95   | 1.10            | 1.1                 | 1.0999       | 0.9527  | 1.0968              | 1.1          | 1.0907  |
| $V_{12}$                 | 0.95   | 1.10            | 1.0821              | 1.0858       | 1.0833  | 1.0887              | 1.1          | 1.0614  |
Table 22. Cont.

| Variables and Parameters | Scenario #16—AHP | Scenario #16—TOPSIS |
|--------------------------|------------------|---------------------|
|                          | Min      | Max      | CHIO | ALO | SSA | CHIO | ALO | SSA |
| W_{gencost}              | 555.43   | 555.43   | 555.43 | 555.39 | 555.43 | 555.36 |
| PV_{gencost}             | 1645.4   | 1658.3   | 1696.8 | 1363.1 | 1439.8 | 1365.3 |
| PVTP_{gencost}           | 156.82   | 156.67   | 156.62 | 156.65 | 156.9  | 156.54 |
| Fuel costs ($/h)         | 30.393   | 30.383   | 30.363 | 31.269 | 30.897 | 31.395 |
| VD (pu)                  | 32,751   | 32,753   | 32,772 | 33,344 | 33,049 | 33,473 |
| $P_{loss}$ (MW)          | 4.9146   | 4.9718   | 4.8841 | 4.9968 | 5.2342 | 5.3727 |
| L-index                  | 0.2321   | 0.2298   | 0.2317 | 0.22947 | 0.22395 | 0.25315 |
| Emissions (ton/h)        | 1.2553   | 1.2581   | 1.3422 | 1.0976 | 1.1198 | 1.0964 |
| Computation time (s)     | 422.21   | 404.68   | 488.94 | 1575.13 | 402.319 | 477.557 |

The fuel cost using the ALO-TOPSIS and emission levels using the CHIO-TOPSIS are more economical and technical than obtained using other approaches, respectively. Figure 16 shows the convergence rate and the Pareto front for the dual objectives for Scenario 16 using the AHP and the TOPSIS, respectively.

Figure 16. The convergence rate and the Pareto front for the dual objectives for Scenario 16 using AHP and TOPSIS: (a) convergence rates using AHP with ALO, SSA, and CHIO; (b) Pareto fronts with ALO, SSA, and CHIO.

5.3. Evaluation of Economical-Environmental-Technical Benefits

In this section, we focus on the economic, environmental, and technical advantages that allow the operator to compromise the various operational elements. Table 23 highlights the economic benefits of saving in fuel costs for the two standard test schemes with and without the integration of RESs using the proposed CHIO technique. This table compares the presented approach to the best approach published in the literature, which corresponds to various objectives. For the IEEE 30-bus, the annual saving differences in fuel cost with and without RESs in Scenarios 1 and 6 are USD 263,062.8 and USD 569,522.6, respectively. For the IEEE 57-bus, the annual saving differences in fuel cost with and without RESs in Scenarios 14 and 16 are USD 78,092,421.6 and USD 78,152,865.6, respectively.
Table 23. Economic benefits of the presented CHIO approach in comparison with other approaches with and without the integration of RESs.

| System | Scenario # | IEEE without RESs | IEEE Integrated with RESs | Saving Difference with and without RESs |
|--------|------------|-------------------|--------------------------|------------------------------------------|
|        |            | Competitive Techniques | Savings ($/h) | Annual Savings ($/yr.) | Competitive Techniques | Savings ($/h) | Annual Savings ($/yr.) | |
| IEEE 30-bus | 1 | PSO-SSO [72] | 798.98 | 0.0550 | 481.80 | CHIO | 768.95 | 12.45 | 109,062 | 30.03 | 263,062.8 |
|          |       | ECBO [73] | 799.035 | | | GWO [76] | 781.40 | | |
|          | 6       | PSO-SSO [72] | 834.804 | 0.110 | 963.60 | CHIO | 769.79 | 12.51 | 109,588 | 65.014 | 569,522.6 |
|          |       | MVO [75] | 834.95 | | | SHADE [76] | 782.30 | | |
| IEEE 57-bus | 14 | PSO-SSO [72] | 41,666.66 | 7.96 | 69,729.6 | CHIO | 32,752 | 4 | 35,040 | 8914.66 | 78,092,421.6 |
|          |       | DA-PSO [37] | 41,674.62 | | | ALO | 32,756 | | |
|          | 16 | PSO-SSO [72] | 41,672.56 | 0.151 | 1,330,644 | CHIO | 32,751 | 2 | 17,520 | 8921.56 | 78,152,865.6 |
|          |       | SSO [72] | 41,824.46 | | | ALO | 32,753 | | |

Table 24 highlights the environmental benefits of saving in emission levels for the two standard test schemes with and without the integration of RESs utilizing the presented CHIO technique. For the IEEE 30-bus, the annual saving differences in emission levels with and without RESs in Scenarios 10 and 13 are 657 ton/h and 963.6 ton/h, respectively. For the IEEE 57-bus, the annual saving differences in fuel cost with and without RESs in Scenarios 14 and 16 are 973.236 ton/h and 917.172 ton/h, respectively.

Table 24. Environmental benefits of the presented CHIO approach in comparison with other approaches with and without the integration of RESs.

| System | Scenario # | IEEE without RESs | IEEE Integrated with RESs | Saving Difference with and without RESs |
|--------|------------|-------------------|--------------------------|------------------------------------------|
|        |            | Competitive Techniques | Savings (ton/h) | Annual Savings (ton/yr.) | Competitive Techniques | Savings (ton/h) | Annual Savings (ton/yr.) | |
| IEEE 30-bus | 10 | PSO-SSO [72] | 0.224 | 0.001 | 8760 | CHIO | 0.14855 | 1.6155 | 14,116.3 | 0.075 | 657 |
|          |       | PSO [72] | 0.225 | | | GWO [76] | 1.76 | | |
|          | 13 | PSO-SSO [72] | 0.256 | 0.001 | 8760 | CHIO | 0.14624 | 0.314 | 2750.6 | 0.11 | 963.6 |
|          |       | SSA [72] | 0.257 | | | SHADE [76] | 0.46 | | |
| IEEE 57-bus | 14 | PSO-SSO [72] | 1.343 | 0.5654 | 4947.25 | CHIO | 1.2322 | 0.026 | 227.76 | 0.11 | 973.236 |
|          |       | DA-PSO [37] | 1.9087 | | | ALO | 1.2581 | | |
|          | 16 | PSO-SSO [72] | 1.36 | 0.24 | ALO | 1.253 | 0.0028 | 24.528 | 0.105 | 917.172 |
|          |       | SSO [72] | 1.60 | | | | | |

From the technical point of view, as seen in Table 25, the CHIO presented has the lowest level in emissions with considerable emission reductions for Scenarios 10, 13, 14, and 16 corresponding to 8760 kg, 4947 tons, and 2100 tons/yr., respectively. Table 24 highlights the technical benefits of saving in power losses for the two standard test systems with and without the integration of RESs using the presented CHIO technique. For the IEEE 30-bus, the annual saving differences in $P_{\text{loss}}$ with and without RESs in Scenarios 1 and 4 are 26,823.12 MW and 6937.044 MW, respectively. For the IEEE 57-bus, the annual saving differences in power losses with and without RESs in Scenarios 14 and 16 are 19,096.8 MW and 21,295.56 MW, respectively.
Table 25. Technical benefits of the presented CHIO method in comparison with other methods with and without the integration of RESs.

| System         | Scenario # | Competitive Techniques | Savings (MW) | Annual Savings (MW) | Competitive Techniques | Savings (MW) | Annual Savings (MW/yr.) |
|----------------|------------|------------------------|--------------|---------------------|------------------------|--------------|--------------------------|
| IEEE 30-bus    | 1          | PSO-SSO [72]           | 8.602        | 0.0112              | CHIO                   | 5.54         | 3.062                    | 26,823.12     |
|                |            | ECBO [73]              | 8.6132       | 0.0112              | CHIO                   | 5.54         | 3.062                    | 26,823.12     |
|                | 4          | PSO-SSO [72]           | 2.858        | 0.023               | CHIO                   | 2.0661       | 0.7919                   | 6937.044      |
|                |            | MVO [75]               | 2.881        | 0.023               | CHIO                   | 2.0661       | 0.7919                   | 6937.044      |
| IEEE 57-bus    | 14         | PSO-SSO [72]           | 14.916       | 0.022               | CHIO                   | 12.736       | 2.18                     | 19,096.8      |
|                |            | DA-PSO [37]            | 14.938       | 0.022               | CHIO                   | 12.736       | 2.18                     | 19,096.8      |
|                | 16         | PSO-SSO [72]           | 15.169       | 0.217               | CHIO                   | 12.738       | 2.431                    | 21,295.56     |

6. Conclusions

This paper proposed an EETD problem for obtaining the best compromise solutions; fuel costs, emission levels, voltage deviation, losses, and stability index of adapted IEEE 30-bus and IEEE 57-bus schemes involved thermal and RESs such as PV, wind, and hybrid PV and tidal-power plants. The major objective is to keep overall fuel costs, active power losses, and pollution levels as low as possible. Various constraints were studied as system limitations. Different optimization methods—the CHIO, the SSA, and the ALO—were utilized for identifying the best alternatives. A total of 16 scenarios were assessed to confirm the potential of the introduced model in resolving the EETD issue. The AHP was employed in computing the weights of the EETD issue. In addition, the TOPSIS procedure was developed to help decision makers use various preferences to find the best alternatives from Pareto results. Finally, the results showed that the CHIO surpasses the techniques studied in resolving the EETD problem. By applying additional optimization techniques, especially hybrid algorithms, the EETD formula may be further researched. Furthermore, it is still a challenge for future study that non-convex EETD problems and uncertainties about load demand combined with uncertainties of all RESs be explored. In addition, IEEE 118 bus, including thermal and stochastic RESs, can be investigated in future works.

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Abbreviations

| Abbreviation | Description                      |
|--------------|----------------------------------|
| ABC          | Artificial bee colony            |
| ABC-DP       | Dynamic population-based artificial bee colony |
| AHP          | Analytical hierarchy process     |
| ALO          | Ant lion optimizer               |
| APSO         | Accelerating particle swarm optimization |
| CCO          | Criss-cross optimizer            |
| Acronym | Description |
|---------|-------------|
| CHIO    | Coronavirus herd immunity optimizer |
| CI      | Consistency index |
| CR      | Consistency ratio |
| DP      | Dynamic programming |
| EETD    | Economical-environmental-technical dispatch |
| ES      | Energy storage |
| ESCO    | Enhanced sine cosine optimizer |
| GF      | Gumbel fitting |
| HIP     | Herd immunity population |
| HIS     | Herd immunity size |
| ISA     | Interior search algorithm |
| LF      | Lognormal fitting |
| MADM    | Multi-attribute decision making |
| MIL     | Mixed-integer linear |
| MIQ     | Mixed-integer quadratic |
| MO      | Multi-objective |
| MOCE/D  | Multi-objective cross-entropy algorithm based on decomposition |
| MOEA/D  | Decomposition-based multi-objective evolutionary algorithm |
| MOHHO   | Multi-objective Harris hawks optimization |
| MOPEO   | Multi-objective population extremal optimization |
| MWOA    | Modified whale optimization algorithm |
| NSGA    | Non-dominated sorting genetic algorithm |
| NSGA-RL | Non-dominated sorting genetic algorithm reinforcement learning |
| ORC     | Overestimation of the reservation cost |
| PDFs    | Probability density functions |
| POZs    | Prohibited operating zones |
| PSO     | Particle swarm optimization |
| PV      | Photovoltaic |
| PVTP    | Photovoltaic and tidal power |
| RC      | Relative closeness |
| RESs    | Renewable energy sources |
| RI      | Average random index |
| SMODE   | Summation based multi-objective differential evolution |
| SO      | Single objective |
| SOS     | Symbiotic organisms search |
| SPG     | Standby power generation |
| SSA     | Salp swarm algorithm |
| TLBO    | Teaching learning-based optimization |
| TOPSIS  | The technique for order preference by similarity to an ideal solution |
| TP      | Tidal power |
| TPGs    | Thermal power generations |
| TVAC    | Time-varying acceleration coefficient |
| UPC     | Underestimation of the penalty cost |
| VD      | Voltage deviation |
| WF      | Weibull fitting |
| WP      | Wind power |

**Nomenclature**

- $\alpha$: The scale factor of the wind turbine
- $\beta$: The shape factor of the wind turbine
- $C_{dpv}$: The direct cost of the photovoltaic system
- $C_{dpvsp}$: The direct cost of the photovoltaic-tidal power system
- $C_{dwp}$: The direct cost of the wind turbine
- $C_{rpv}$: The reserve capacity cost of the photovoltaic system
- $C_{rpvsp}$: The reserve capacity cost of the photovoltaic-small hydro system
- $C_{rwp}$: The reserve capacity cost of the wind turbine
- $C_{spv}$: The storage units cost of the photovoltaic system
- $C_{spvsp}$: The storage units cost of the photovoltaic-tidal power system
$C_{SWP}$  The storage units cost of the wind turbine
$C_{tot}$  The total cost of the fuel or generation
$C_{tot_{PV}}$  The total cost of the photovoltaic generation unit
$C_{tot_{PVTP}}$  The total cost of the photovoltaic-tidal power unit
$C_{tot_{WP}}$  The total cost of the wind turbine generation unit
$C_{tot_{(P_{TPGs})}}$  The total cost of the thermal power generations
$C_{tot_{(P_{RESs})}}$  The total cost of the renewable energy sources
$\delta_{ij}$  The phase difference between the buses $i$ and $j$
$\eta_w$  Tidal efficiency turbines’
$E_{tot}$  The total emission
$f_v(v)$  The probability of wind speed
$f$  Friction factor
$G$  Solar irradiance
$G_{std}$  Standard solar irradiance
$G_q(ij)$  The transconductance of branch $q$ connected to bus $i$ and bus $j$
$H_w$  The effective pressure head for the water
$K_{d_{WP}}$  The direct cost parameter of the wind turbine
$K_{r_{WP}}$  The reserve capacity cost parameter of the wind turbine
$K_{S_{WP}}$  The storage unit cost parameter of the wind turbine
$\lambda$  Location parameter of the river
$L$-index  Stability index
$Max_{_Itr}$  Maximum iteration number
$N_G$  Number of generator buses
$N_L$  Number of load buses
$nl$  Number of branches in the network
$P_{loss}$  Power loss
$P_{PV_{act}}$  The actual power of the photovoltaic system
$P_{PV_{r}}$  The rated power of the photovoltaic system
$P_{PV_{sch}}$  The scheduled power of the photovoltaic system
$P_{PV_{TPact}}$  The actual power of the photovoltaic small hydro system
$P_{PV_{TPsch}}$  The scheduled power of the photovoltaic-small hydro system
$P_{min_{iTPG}}$  The minimum power of the $i$th thermal power generator unit
$P_f(Q_w)$  The yield power from the tidal power plant
$P_{WP_{act}}$  The actual power of the wind turbine
$P_{WP_{r}}$  The rated power of the wind turbine
$P_{WP_{sch}}$  The scheduled power of the wind turbine
$Q_w$  River flow rate
$R_c$  Operation irradiance
$\rho_w$  Water density
$S_{LP}$  The branches’ capacity limit
$T_s$  The standard temperature in kelvin
$v$  The wind speed
$V_G$  The voltage of the $i$th on generator bus
$v_{in}$  Cut-in speed of the wind turbine
$V_L$  The voltage of the $p$th on load bus
$v_{out}$  Cut-out speed of the wind turbine
$v_{r}$  The rated speed of the wind turbine

### Appendix A

**Table A1.** Direct, reserve, and standby cost coefficients for RESs uncertainties.

|                        | WP       | PV       | PVTP     |
|------------------------|----------|----------|----------|
| Direct cost coefficients ($/MW$) | $K_{d_{WP}} = 1.70$ | $K_{d_{PV}} = 1.60$ | $K_{d_{PVTP}} = 1.50$ |
| Reserve cost coefficients ($/MW$)  | $K_{r_{WP}} = 3.00$ | $K_{r_{PV}} = 3.00$ | $K_{r_{PVTP}} = 3.00$ |
| Penalty cost coefficients ($/MW$)   | $K_{S_{WP}} = 1.40$ | $K_{S_{PV}} = 1.40$ | $K_{S_{PVTP}} = 1.40$ |
Table A2. Control parameter setting of CHIO, ALO, and SSA algorithms for the testing power system.

| Optimization Techniques | ALO | SSA | Proposed (CHIO) |
|-------------------------|-----|-----|-----------------|
| Max. iteration          | 300 | 300 | 300             |
| No. of population       | 50  | 50  | 50              |
| Control parameters      | $\text{rand} = [0, 1]$ | $K_{\text{min}} = 0.43$ | $C_0 = 1$ |
|                         |     | $K_{\text{max}} = 0.85$ | $B_R = 0.05$ |
| Independent runs        | 30  | 30  | 30              |

Table A3. Decision variables of the IEEE 30-bus system.

| Decision Variables | Bounds | |
|--------------------|--------|------|
| $P_{TPG2}$         | 20     | 80   |
| $P_{TPG5}$         | 10     | 60   |
| $P_{TPG8}$         | 10     | 35   |
| $P_{TPG11}$        | 10     | 60   |
| $P_{TPG13}$        | 10     | 60   |
| $V_1$              | 0.96   | 1.10 |
| $V_2$              | 0.96   | 1.10 |
| $V_5$              | 0.96   | 1.10 |
| $V_8$              | 0.96   | 1.10 |
| $V_{11}$           | 0.96   | 1.10 |
| $V_{13}$           | 0.96   | 1.10 |

Table A4. Decision variables of the IEEE 57-bus system.

| Decision Variables | Bounds | |
|--------------------|--------|------|
| $P_{TPG1}$         | 80     | 200  |
| $P_{TPG2}$         | 30     | 100  |
| $P_{TPG3}$         | 40     | 140  |
| $P_{TPG6}$         | 30     | 100  |
| $P_{TPG8}$         | 100    | 550  |
| $P_{TPG9}$         | 30     | 100  |
| $P_{TPG12}$        | 100    | 410  |
| $V_1$              | 0.95   | 1.10 |
| $V_2$              | 0.95   | 1.10 |
| $V_3$              | 0.95   | 1.10 |
| $V_6$              | 0.95   | 1.10 |
| $V_8$              | 0.95   | 1.10 |
| $V_{11}$           | 0.95   | 1.10 |
| $V_{12}$           | 0.95   | 1.10 |

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