
Research article

Economic and environmental optimization of hybrid wind-combined heat and power dispatch: A static and dynamic analysis

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Abstract: This study introduces the Mexican Axolotl Optimization (MAO) algorithm to address the combined heat and power economic-emission dispatch (CHPEED) problem. The objective is to optimize power and heat generation from online units in a power system, including wind power plants under deterministic conditions, over a specified timeframe, to reduce operating costs and emissions simultaneously while satisfying all generators' limits. The effectiveness of the MAO approach was evaluated through extensive testing on three CHPD issues: static economic environmental dispatch, dynamic economic environmental dispatch (DEED), and hybrid wind-CHPDEED. The inclusion of the practical constraints, such as valve point loading effects (VPLE), transmission losses, feasible operating regions (FOR), and ramp rate limits (RRL), renders MO-CHPDEED problems with non-convex characteristics. A weighting method was employed to convert the MO-CHPD issues into single-objective optimization problems. Standard test systems with 5 and 7 units were employed to

demonstrate the algorithm's performance across varying levels of complexity. The numerical results were compared with those obtained using various other optimization methods from the literature. The MAO approach demonstrates competitive performance, achieving the best results in environmental dispatch and MO-CHPD scenarios, while showing good performance in economic dispatch, despite some methods achieving lower costs.

Keywords: CHP-units; CHP dynamic economic environmental dispatch; Mexican axolotl optimization; multi-objective optimization; weighting method; wind power plants

Mathematics Subject Classification: 68T20, 68W50, 90C59, 65K10

1. Introduction

Combined heat and power (CHP) systems, commonly known as co-generation systems, are gaining popularity for enhancing energy efficiency and cutting emissions. CHP units produce electricity and heat simultaneously from a single fuel source [1]. The electricity powers homes and businesses, while the generated heat is utilized for building heating or hot water supply [1]. Compared to power plants, CHP systems are more efficient because they harness waste heat to generate electricity, thereby reducing energy costs, enhancing energy security, lowering peak electricity demand, and creating jobs [2]. CHP generation units are recognized for their efficiency, reliability, cleanliness, sustainability, and cost-effectiveness. They offer a technology that can be applied in several uses [3]. The ability of CHP technology to generate electricity and heat simultaneously has been lauded as a substantial leap in energy efficiency. It reaches up to 90% [4], far surpassing the efficiency of traditional thermal power plants, which typically hover around 60% [5]. Operating costs for CHP systems also display significant reductions, dropping by 10%–40% [6]. These advantages, paired with a noteworthy decrease in pollution emissions by 13%–18% [7], have made CHP a popular choice for achieving optimal operation.

The economic and environmental benefits of CHP units are attractive to many businesses and communities. However, some challenges must be overcome to encourage wider adoption [3]. One obstacle is the high initial cost of installing CHP systems, which can be higher than that of traditional power plants due to specialized equipment and expertise. This financial challenge makes it difficult for businesses and communities to justify investing in CHP [8]. Additionally, the lack of clear regulatory guidelines for CHP systems presents another barrier [9]. In many regions, CHP systems do not receive the same incentives as other renewable energy technologies. This can pose difficulties for CHP systems competing with other energy generation forms [8]. Integrated energy system (IES) combined power-hydrogen-heat cogeneration (CPHH-IES) exhibit several advantages over traditional CHP systems [10]. CPHH-IES provides enhanced efficiency, long-term energy storage capabilities, reduced carbon emissions, improved grid stability, economic viability, and better integration of renewable energy sources [10]. As part of IES, energy storage systems (ESS) serve as both electrical and thermal storage solutions in CHP systems, significantly enhancing system flexibility, reliability, and economic viability, by storing excess energy and releasing it during periods of energy deficiency [11].

The need to balance economic benefits and environmental protection has led to the development of CHP economic emission dispatch (CHPEED) [12,13]. CHPEED addresses this challenge by integrating cost minimization and emission reduction. CHPEED aims to find the optimal heat-power operating point that satisfies the heat and power demands while ensuring reasonable fuel consumption and reduced emissions [14]. CHP systems can contribute to sustainable and eco-friendly energy production. However, the CHPEED models properties are characterized by their nonlinearity and non-convexity. Non-smoothness poses challenges when using traditional methods to find optimal solutions [15]. Methods such as Lagrange multiplier, linear programming, quadratic programming, and dynamic programming have been employed in the past [16,17]. The CHP dynamic economic dispatch (CHPDED) problem is an optimization technique employed to optimize the power and heat schedule of online thermal plants based on heat and electricity demands within specific time intervals [18]. When emissions are considered in the CHPDED problems, they become CHPDEED. Such issues are treated as multiobjective optimization (MOO) problems, considering multiple constraints [19].

1.1. Literature review

The challenge of CHPED optimization has attracted significant research efforts. A wide range of approaches and techniques has been explored to address this complex problem. These approaches can be broadly categorized into various groups: classical methods, stochastic search techniques, and hybrid approaches that combine elements of both [20].

To address CHPED problems, classical optimization typically employs established mathematical approaches such as Lagrangian relaxation [21], Benders decomposition [22], nonlinear mixed-integer programming [23], branch and bound algorithm [24], and dual partial-separable programming technique [25]. Despite being fast, reliable, and producing consistent cost results [26], these derivative-based techniques face significant limitations, namely their sensitivity to initial starting points and objective function behavior. Additionally, coupled with the nonlinear, non-convex, and non-smooth characteristics of CHPED issues, means they frequently struggle to locate the global optimum or near-optimal solutions [27].

Evolutionary and meta-heuristic methods are widely employed to address the CHPED problem. Algorithms have been proposed, like differential evolutionary (DE) [28], neighborhood-based differential evolution algorithm with direction-induced strategy (NDIDE) [29], real-coded genetic algorithm with random walk-based mutation (RCGA-CRWM) [30], crisscross optimization algorithm (COA) [31], and stochastic fractal search (SFS) algorithm [32]. These methods have been classified as evolutionary algorithms (EAs). In [30,33], a diverse range of swarm-intelligence-based optimization algorithms were discussed. Building on this, enhanced PSO variants, cuckoo search (CS) [34], the Whale optimization method [35], war optimization [36], the walrus algorithm [37], fractional-order velocity-pausing PSO [38], the moth flame optimization [39,40], and Gbest differential ant bee optimization [41], have been employed to different engineering optimization problems.

Human-based algorithms, including Social cognitive optimization [42], analysis of heuristic optimization [43], novel Heap-based optimizer [44], Improvement of the Fitness-Distance Balance-Based Supply-Demand Optimization Algorithm [45], and Harmony search algorithm (HSA) [46], have been utilized for solving the combined heat and power economic dispatch problem. Physics-based techniques, which rely on fundamental laws of nature like mass and energy balance, are widely

employed to handle CHPD problems. Examples include the Heat transfer search algorithm, the Rao-I optimization algorithm, neural-network-based optimization, and the gravitational search algorithm (GSA), cited respectively in [47–50]. Some derivative-free methods that do not require a good starting point and can escape from local minima solutions [33] still cannot guarantee finding the optimal solution, do not provide meaningful measurements regarding the distance from the global optima, and are susceptible to premature convergence [26].

Scholars have also developed hybrid meta-heuristic algorithms as another category to address the CHPED problems. Examples include the Lagrange relaxation-based alternating iterative (AI) algorithm [51], the hybrid heap-based and jellyfish search algorithm (HBJSA) [52], the hybrid modified grasshopper optimization algorithm (MGOA) and the improved Harris hawks optimizer (IHHO) named MGOAIHHO [53], the hybrid chameleon swarm algorithm (CSA) and mayfly optimization (MO) called CSMO [54], the fuzzy adaptive ranking-based crow search algorithm (FRCSA) with modified artificial bee colony (ABC), known as (FRCSA-ABC) [55], the hybrid firefly and self-regulating PSO (FSRPSO) [56], and the basic Jaya algorithm and Rao 3 algorithm [57].

In recent years, numerous studies have focused on the MO-CHPEED issue. The reinforcement-learning-based multi-objective differential evolution (RLMODE) algorithm [58], time-varying acceleration PSO (TVAC-PSO) [59], non-dominated sorting genetic algorithm-II (NSGAII) [60], indicator and crowding distance-based evolutionary algorithm (IDBEA) [61], Harris Hawks optimization (HHO) [62], and multi-objective multi-verse optimization algorithm (MOMVO) [63] have all been investigated and implemented to tackle this challenge in many scale systems, respectively. Reference [64] proposed a hybrid approach combining NSGA-II and MOPSO to solve the MO-CHPEED problem in two typical test systems in which NSGA-II handles the exploration phase and MOPSO concentrates on the exploitation phase. Scholars in [65] introduced a two-stage methodology for finding optimal compromise solutions in small-scale systems, by combining θ -dominance-based evolutionary algorithm (θ -DEA) with the integrated decision-making technique FCM-GRP. Additionally, [66] employed a dynamically controlled whale optimization approach (DCWOA) to solve the MO-CHPEED problem in a fuzzy environment, while [67] developed an improved bare-bones MO-PSO (IBB-MOPSO) for the same purpose. Scholars in [68] designed an exchange market algorithm (EMA) with fuzzy satisfying techniques to address the MO-CHPEED problem and determine the best compromise solutions. The grasshopper optimization algorithm (GOA) in [69] was employed to handle the multi-zone CHPEED issue under practical constraints and wind uncertainty. A multi-objective membrane search algorithm (MOMSA) was suggested in [70] for solving the CHPEED issue, and the authors in [71] applied a dynamic switched crowding-based multi-objective symbiotic organism search (DSC-MOSOS) algorithm to address the CHPEED problem. The CHPDEED issue, an extension of the CHPEED problem, incorporates various practical constraints [18,19,72].

Many optimization approaches have been developed and implemented to address the MO-CHPDEED problems, like the enhanced firefly algorithm (EFA) in [15], the hybrid differential evolution (DE) and sequential quadratic programming (SQP) approach (DE-SQP) in [72], and the double benders decomposition approach (DBD) in [73]. A hybrid PSO and SQP was designed in [74] to handle the MO-CHPEED while considering power losses and VPL impacts. Scholars in [75] suggested a global NSGA-II based on a crossover with negative exponential distribution (GNSGA-II) for the CHPDEED problem in the presence of renewable energy resources (RES). The researchers in [76] presented the Bernstein-search differential evolution (BSDE) algorithm to obtain the best solutions of a bi-objective CHPDEED with integrated energy storage elements. NSGA-III and strength

Pareto evolutionary algorithm 2 (SPEA 2) have been discussed in [77] to study the multi-county CHPDEED incorporating RES and electric vehicles (EV) parking. Proposed in [78], a two-stage sequential framework jointly schedules Generation–Grid–Load–Storage (GGLS) resources in a new-type power system (NTPS), leveraging a modified Feedback Wolf Pack Algorithm (FWPA) for efficient mixed-variable problem solving. All metaheuristic optimization methods discussed above, especially nature-inspired approaches, share common limitations and suffer from slow exploitation. These encompass challenges in handling constraints and the tendency for search algorithms to prematurely converge on solutions that are not the true global optimum [20]. Many scholars have shown that adjusting the algorithm's parameter settings can lead to a significant increase in both the total cost and the emissions of the CHP system, highlighting the importance of optimal parameter tuning to achieve effective results [55]. Conversely, improper parameter settings can result in a slow convergence rate.

1.2. Contribution and paper organization

In 2021, Y. Villandas-Rey et al. developed an optimization approach inspired by the life of the axolotl, known as Mexican axolotl optimization (MAO) [79]. This algorithm emulates the behavior of Mexican axolotls to find the global optima. Motivated by the MAO approach's ability and successful performance in handling location determination of EVs [80], elimination of nonlinearities in energy harvesting network [81], renewable energy sources [82] and other complex optimization problems [83–85], this study applies the MAO method to address the MO-CHPEED/CHPDEED issues. The main contributions of this work include:

- A comprehensive review of heuristic optimization methods applied to the CHPED, CHPEED, and CHPDEED problems.
- The formulation of a MO wind-based CHPDEED problem, converted into a single-objective form via a weighting method.
- An adaptation of the MAO algorithm to CHP dispatch including a feasibility projection for CHP-FOR alongside adaptive constraint-handling mechanisms.
- An evaluation of the MAO algorithm across static, dynamic, and hybrid wind-CHP dispatch scenarios on 5-unit and 7-unit test systems, accounting for VPLE, transmission losses, RRL, and FOR constraints.
- A comparison against established techniques from the literature to validate the algorithm's ability to determine the global optimum of such problems.

The remaining sections of this paper are structured as follows: Section 2 formulates the objectives and constraints of the wind-based CHPDEED problem. Section 3 describes the MAO approach and presents a flowchart of the algorithm. Section 4 presents experiment on two test systems and compares MAO with several representative algorithms. Finally, Section 5 summarizes this research.

2. Problems formulation

The mathematical model of CHPDEED comprises four types of generating systems: conventional thermal units (CTU), CHP units, heat-only units (H), and wind power plants. CTUs and wind turbines generate electrical power, heat-only units generate heat, and CHP units generate both. The objective functions of the CHPEED/CHPDEED problems are to simultaneously optimize the committed

system's generation costs and emissions while meeting the predicted heat and power demands over specific time intervals, subject to practical constraints. The objective functions and constraints of the problem are formulated as follow [18,19,72]:

2.1. Thermal units

Generally, the production cost function for the CTU may be expressed as a quadratic function [86]. However, a more precise formulation takes into account VPLe. These effects, which result from the stepwise operation of steam valves in the CTU, lead to nonlinear input-output (I/O) characteristics. Thermal power plants operate most efficiently at valve-points, just before the next valve opens. The cost function that incorporates VPLe is expressed as follows [87,88]:

$$C_i^{CTU}(P_{i,t}^{CTU}) = a_i + b_i \cdot P_{i,t}^{CTU} + c_i \cdot (P_{i,t}^{CTU})^2 + \left| e_i \cdot \sin \left\{ f_i \cdot (P_{i,t}^{\min} - (P_{i,t}^{CTU})) \right\} \right| \quad (1)$$

where a_i , b_i , and c_i are the fuel cost coefficients corresponding of thermal generating unit i , e_i , and f_i are cost coefficients of i^{th} generator due to VPLe; $C_i^{CTU}(P_{i,t}^{CTU})$ represents the fuel cost in (\$/h) of i^{th} thermal unit with output $P_{i,t}^{CTU}$ at time t ; $P_{i,t}^{TU}$ represents the minimum capacity of generator i .

The emission of the CTU is given by [87]:

$$E_i^{CTU}(P_{i,t}^{CTU}) = \alpha_i + \beta_i P_{i,t}^{CTU} + \gamma_i (P_{i,t}^{CTU})^2 + \eta_i \exp(\delta_i P_{i,t}^{CTU}) \quad (2)$$

where, α_i , β_i , γ_i , η_i and δ_i are the emission coefficients of generator i , and $E_i^{CTU}(P_{i,t}^{CTU})$ represents the total emissions to generate $P_{i,t}^{CTU}$.

2.2. CHP units

The CHP unit generates both power and heat. Thus, the fuel cost function is the product of both outputs. Typically, this is represented as a convex cost function [15,18,20,72], which is given as:

$$C_k^{CHP}(P_{k,t}^{CHP}, H_{k,t}^{CHP}) = a_k + b_k P_{k,t}^{CHP} + c_k (P_{k,t}^{CHP})^2 + d_k H_{k,t}^{CHP} + e_k (H_{k,t}^{CHP})^2 + f_k (P_{k,t}^{CHP} \times H_{k,t}^{CHP}) \quad (3)$$

where, a_k , b_k , c_k , d_k , e_k , and f_k are the fuel cost coefficients of CHP generator k , and $C_k^{CHP}(P_{k,t}^{CHP}, H_{k,t}^{CHP})$ is the production fuel cost of CHP system k to generate heat $H_{k,t}^{CHP}$ and power $P_{k,t}^{CHP}$ at time t .

The total emissions from CHP units are only determined by the power output [15,60,72], reported as follows:

$$E_k^{CHP}(P_{k,t}^{CHP}) = (\alpha_k + \beta_k) P_{k,t}^{CHP} \quad (4)$$

where α_k and β_k are the emission function coefficients of CHP unit k . In a CHP unit, heat and power production are interdependent and mutually constraining.

Figure 1 illustrates the FOR of CHP unit [56,60,67].

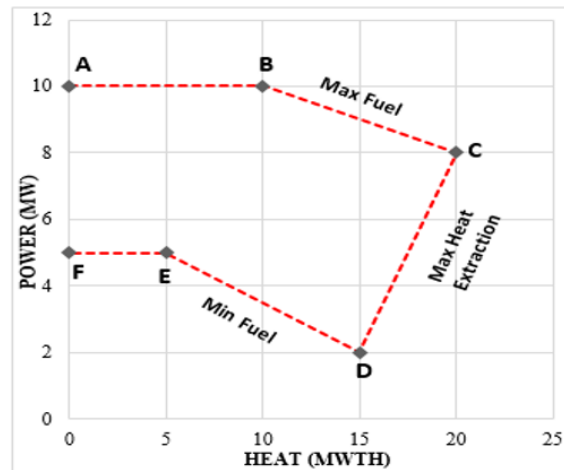


Figure 1. Possible operating area of CHP unit.

2.3. Heat-only units

These systems generate solely heat, and the cost function is expressed by [4,38,74]:

$$C_l^H(H_{l,t}^H) = a_l + b_l H_{l,t}^H + c_l (H_{l,t}^H)^2 \quad (5)$$

where, the constants a_l , b_l , and c_l are the fuel cost coefficients of heat-only unit l , and $H_{l,t}^H$ is the heat produced from heat generator l at time t .

The emission function is proportional to their heat output [72,74]:

$$E_l^H(H_{l,t}^H) = (\alpha_l + \beta_l) H_{l,t}^H \quad (6)$$

where, α_l and β_l are the emissions coefficients of heat-only system l .

Furthermore, by incorporating RES into power generation, we can significantly reduce both fuel costs and pollutant emissions.

2.4. Wind power plant integration

By incorporating wind turbines into power generation, we can significantly reduce both fuel costs and pollutant emissions. The power output of a wind generator is influenced by wind speed availability and the turbine's specific characteristics and efficiency [89]. The hourly output power $P_{w,t}$ of the wind turbine can be expressed as follows [90]:

$$P_{w,t} = \frac{1}{2} \rho \lambda_w A \eta_w V^3 \quad (7)$$

where ρ is the air density (assumed to be 1 kg/m^3), λ_w is the coefficient of the wind turbine generator, A is the wind-swept area, η_w is the wind turbine efficiency, and V is the velocity of the wind generator.

Wind power plants require an initial investment in equipment as well as ongoing operation and maintenance (O&M) costs. Their cost function $F(P_{w,t})$, can be calculated as follows [91,92]:

$$F(P_{w,t}) = P_{w,t} \times (AC \cdot I^P + G^E) \quad (8)$$

where, $P_{w,t}$ is the hourly power generation of the wind turbine (kW), AC is the annuitization coefficient, I^P is the ratio of investment costs to established power in (\$/kWh), and G^E is the O&M costs in (\$/kWh). Annuitization coefficient can be calculated using the following formula [91,92]:

$$AC = \frac{r}{1 - (1 + r)^{-N}} \quad (9)$$

where r is the interest scale, taken as 0.09 for the base case, and N is the investment duration taken as 20 years [91]. For this research, we assumed that the O&M costs per unit of generated energy (G^E) and the investment costs per unit of installed power (I^P) are approximately 1400 \$/kWh and 0.016 \$/kWh, respectively [93]. So, the cost function of a wind farm (\$/h) is calculated as [92,93]:

$$F(P_{w,t}) = 153.3810 \times P_{w,t} . \quad (10)$$

Figure 2 outlines the MAO-based process for optimal scheduling of a hybrid wind-CHP system.

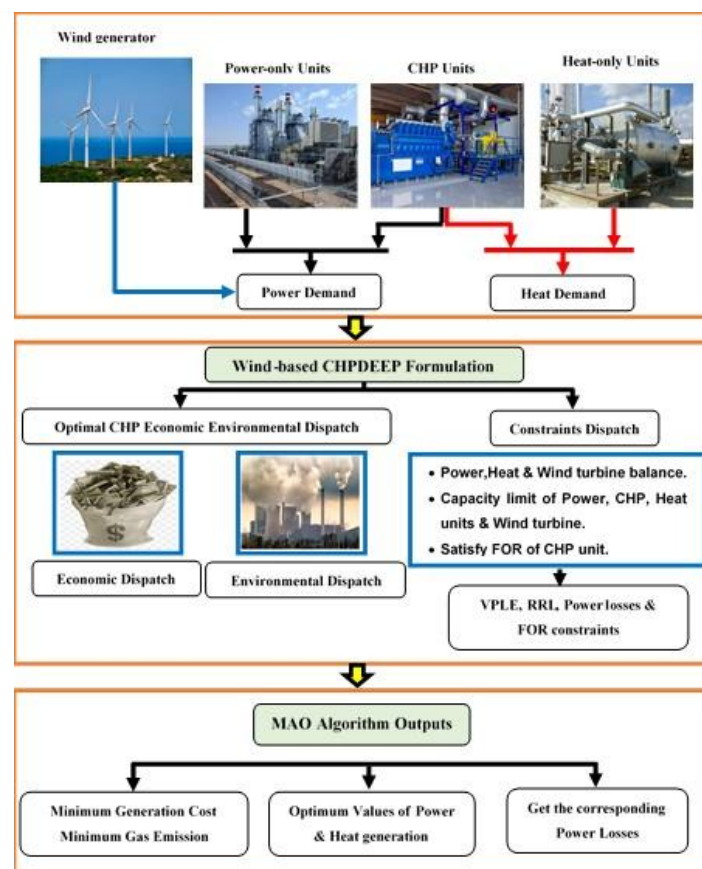


Figure 2. The process of optimal scheduling of a hybrid wind-CHP system using the MAO method.

2.5. Objective functions

The total fuel cost of the three types of generating units over the scheduling period $[0, T]$ is represented by [71,74]:

$$C(PH) = \sum_{t=1}^T \left(\sum_{i=1}^{T_p} C_i^{CTU} (P_{i,t}^{CTU}) + \sum_{k=1}^{T_c} C_k^{CHP} (P_{k,t}^{CHP}, H_{k,t}^{CHP}) + \sum_{l=1}^{T_h} C_l^H (H_{l,t}^H) \right). \quad (11)$$

Similarly, for thermal CHP, and heat units, the total emission function is given by [71]:

$$E(PH) = \sum_{t=1}^T \left(\sum_{i=1}^{T_p} E_i^{CTU} (P_{i,t}^{CTU}) + \sum_{k=1}^{T_c} E_k^{CHP} (P_{k,t}^{CHP}) + \sum_{l=1}^{T_h} C_l^H (H_{l,t}^H) \right) \quad (12)$$

$$\left\{ \begin{array}{l} PH = (PH_1, PH_2, \dots, PH_t, PH_T)' \\ PH_t = (P_t^{CTU}, P_t^{CHP}, H_t^{CHP}, H_t^H)' \\ P_t^{CTU} = (P_{1,t}^{CTU}, P_{2,t}^{CTU}, \dots, P_{T_p,t}^{CTU})' \\ P_t^{CHP} = (P_{1,t}^{CHP}, P_{2,t}^{CHP}, \dots, P_{T_c,t}^{CHP})' \\ H_t^{CHP} = (H_{1,t}^{CHP}, H_{2,t}^{CHP}, \dots, H_{T_c,t}^{CHP})' \\ H_t^H = (H_{1,t}^H, H_{2,t}^H, \dots, H_{T_h,t}^H)' \end{array} \right. \quad (13)$$

where, the prime (') denotes the transpose of a vector. T, T_p, T_c , and T_h are the total number of scheduling intervals, total number of CTU, total number of CHP systems, and the total number of heat-only units, respectively [73].

2.6. Constraints

The objective functions of the problems must be addressed by considering various equality and inequality constraints related to operations and the power network. These constraints include the CTU's VPLe, power losses, generation capacity and RRL of production units, and the heat-power dependency of cogeneration units.

2.6.1. Equality constraints

▪ Power generation and demand equilibrium constraint

$$\sum_{i=1}^{T_p} P_{i,t}^{CTU} + \sum_{k=1}^{T_c} P_{k,t}^{CHP} + P_{w,t} = P_{D,t} + P_{loss,t} \quad t = 1, \dots, T. \quad (14)$$

▪ Heat generation and demand equilibrium constraint

$$\sum_{k=1}^{T_c} H_{k,t}^{CHP} + \sum_{l=1}^{T_h} H_{l,t}^H = H_{D,t} . \quad (15)$$

2.6.2. Inequality constraints

▪ CTU operation limits

$$P_{i,\min}^{CTU} \leq P_{i,t}^{CTU} \leq P_{i,\max}^{CTU} \quad i = 1, \dots, T_p . \quad (16)$$

▪ CHP units operating limits

$$P_{k,\min}^{CHP} \left(H_{k,t}^{CHP} \right) \leq P_{k,t}^{CHP} \leq P_{k,\max}^{CHP} \left(H_{k,t}^{CHP} \right) \quad k = 1, \dots, T_c . \quad (17)$$

$$H_{k,\min}^{CHP} \left(P_{k,t}^{CHP} \right) \leq H_{k,t}^{CHP} \leq H_{k,\max}^{CHP} \left(P_{k,t}^{CHP} \right) . \quad (18)$$

▪ Heat-only unit's operation limits

$$H_{l,\min}^H \leq H_{l,t}^H \leq H_{l,\max}^H \quad l = 1, \dots, T_h . \quad (19)$$

▪ Ramp rate limits

$$-DR_i^{CTU} \leq P_{i,t+1}^{CTU} - P_{i,t}^{CTU} \leq UR_i^{CTU} \quad i = 1, \dots, T_p . \quad (20)$$

$$-DR_k^{CHP} \leq P_{k,t+1}^{CHP} - P_{k,t}^{CHP} \leq UR_k^{CHP} \quad k = 1, \dots, T_c . \quad (21)$$

▪ Wind generators operation limits

$$0 \leq P_{w,t} \leq P_{w,\max} \quad t = 1, \dots, T . \quad (22)$$

$P_{loss,t}$ is approximately calculated by Kron's formula [86] as follows:

$$P_{loss,t} = \sum_{i=1}^{T_p+T_c} \sum_{j=1}^{T_p+T_c} PL_{i,t} \cdot B_{i,j} \cdot PL_{j,t} , \quad (23)$$

where

$$PL_{i,t} = \begin{cases} P_{i,t}^{CTU} , & i = 1, \dots, T_p \\ P_{i-T_p,t}^{CHP} , & i = T_p + 1, \dots, T_p + T_c \end{cases} . \quad (24)$$

$P_{w,t}$ is the total wind power generation at time t in (MW);

$P_{D,t}$ is the total system power demand at time t in (MW);

$P_{loss,t}$ is the total system power losses at time t in (MW);

$H_{D,t}$ is the total system heat demand at time t in (MWth);

$P_{i,max}^{CTU}$ is the maximum power limits of thermal generator i in (MW);

$P_{k,min}^{CHP}(H_{k,t}^{CHP})$ and $P_{k,max}^{CHP}(H_{k,t}^{CHP})$ are the minimum and maximum power limits of CHP system k , respectively, in (MW). Both parameters are functions of $(H_{k,t}^{CHP})$, the heat produced;

$H_{k,min}^{CHP}(P_{k,t}^{CHP})$ and $H_{k,max}^{CHP}(P_{k,t}^{CHP})$ are the heat limits capacities of CHP system k in (MWth), which are functions of the output power $(P_{k,t}^{CHP})$;

$H_{l,min}^H$ and $H_{l,max}^H$ are the lower and upper boundary heat of the heat-only unit l , respectively, in (MWth);

DR_i^{CTU} and UR_i^{CTU} are the maximum ramp down and up rates of thermal generator i , respectively;

DR_k^{CHP} and UR_k^{CHP} are the maximum ramp down and up rates of CHP system k , respectively;

$B_{i,j}$ is the ij^{th} element of the loss coefficient square matrix of size $T_p + T_c$.

In this study, we employed a weighting method to address the MO-CHPEED problem. This method involves combining multiple objective functions into a single objective function by assigning weights to each function [94]. The two objective functions (Eqs (11) and (12)) were converted into a single objective function via a weighting factor ($w \in [0.1]$). The resultant objective function can be formulated as:

$$\min F_{total} = \min[w * (C(PH) + F(P_{w,t})) + (1 - w) * E(PH)]. \quad (25)$$

For any infeasible solution, a penalty term is added to the objective function:

$$F_{penalized} = F_{objective} + \lambda \times \sum_{j=1}^{N_c} \max(0, g_j(x))^2, \quad (26)$$

where $\lambda \in [100, 10,000]$ is the penalty factor (dynamically adjusted over iterations), and $g_j(x)$ is the constraint violations (including capacity limits, RRL, and FOR violations). Note that if $w = 1$, then formula (25) leads to the CHP economic dispatch; in this case, the author wants to minimize production cost alone. However, if $w = 0$, then function (25) leads to CHP environmental dispatch, where the modeler seeks to minimize emissions alone. It is presumed, for the aim of this article that equal weights are given to both objective functions; thus, $w=0.5$.

3. Materials and methods

The MAO algorithm is a bio-inspired optimization technique that primarily borrows from the axolotl's unique biology [79]. It draws inspiration from the axolotls' birth, reproduction, and tissue-regeneration processes (including sex and coloration), as well as their aquatic life cycle. As axolotls are a species with separate sexes, both males and females are present. Furthermore, axolotls change color to camouflage themselves and alter coloration on other parts of their bodies to avoid predators. The MAO technique operates in four iterative stages, abbreviated as TIRA, Transition from larvae to adult stage; injury and restoration; reproduction; and assortment. A clear and detailed pseudocode

representation of the MAO method is provided in Figure 3. This article applies the MAO approach to solve the static and dynamic economic emission dispatch of a combined heat and power system. The step-by-step procedure for solving the CHP problem using MAO is as follows [80,90]:

Step 1: Initialization. Set parameters of MAO

The main parameters of MAO include [80] population size, male and female populations, damage probability, regeneration probability, differential constant, tournament size, crossover probability, and termination criteria (maximum iteration value).

Step 2: Random generation

The initial independent variables of the issue are generated randomly. In this stage, the real power output of CTU ($(T_p - 1)$ generators), the output of the heat-only unit ($(T_h - 1)$ units), and real power and heat outcomes of the CHP systems (T_c units) of the CHPEED/CHPDEED problems are generated randomly within their specified operating limits as follows:

$$P_{i,j}^{CTU} = P_{j,\min}^{CTU} + rand(0,1) \times (P_{j,\max}^{CTU} - P_{j,\min}^{CTU}) \quad i = 1, \dots, T_p - 1, \quad (27)$$

$$P_{i,j}^{CHP} = P_{j,\min}^{CHP} (H_{i,j}^{CHP}) + rand(0,1) \times (P_{j,\max}^{CHP} (H_{i,j}^{CHP}) - P_{j,\min}^{CHP} (H_{i,j}^{CHP})), \quad j = 1, \dots, T_c, \quad (28)$$

$$H_{i,j}^{CHP} = H_{j,\min}^{CHP} (P_{i,j}^{CHP}) + rand(0,1) \times (H_{j,\max}^{CHP} (P_{i,j}^{CHP}) - H_{j,\min}^{CHP} (P_{i,j}^{CHP})), \quad j = 1, \dots, T_c, \quad (29)$$

$$H_{i,j}^H = H_{j,\min}^H + rand(0,1) \times (H_{j,\max}^H - H_{j,\min}^H) \quad j = 1, \dots, T_h - 1, \quad (30)$$

where, $rand()$ is random number, uniformly distributed between 0 and 1. To satisfy both the heat demand and power demand's equality constraints, the power production of the T_p th CTU and heat output of the T_h th heat-only system are calculated as follows:

$$P_{T_p} = P_{D,t} + P_{loss,t} - P_{w,t} - \sum_{j=1}^{T_p-1+T_c} P_{j,t}, \quad (31)$$

$$H_{T_h} = H_{D,t} - \sum_{j=1}^{T_h-1+T_c} H_{j,t}. \quad (32)$$

Step 3: Fitness computation

Calculate the fitness value for each solution using the objective functions (Eq (25)). The objective function should be minimized while meeting all constraints.

Step 4: Classification of male and female population

Due to axolotls developing based to their sex, individuals are classified into two subpopulations (male and female populations) [82] randomly.

Step 5: Transition from larvae to adult state

The algorithmic process begins with a transition from the larval (exploration) stage to the adult (exploitation) stage. During this transition, the objective function assigns inverse transition probabilities to "male" and "female" individuals within the population. At this point, choose the promising solutions (best males) alongside diverse solutions (females) based on the objective function [79]. Determine the inverse probability of transition for each individual as illustrated in Eqs (33) and (34).

$$pm_j = \frac{om_j}{\sum om_j}, \quad (33)$$

$$pf_j = \frac{of_j}{\sum of_j}. \quad (34)$$

If $pm_j < u$ and $pf_j < u$, update the individuals axolotls based on their body restoration, as given in Eqs (33) and (34), respectively [79,80].

$$m_{ji} = m_{ji} + (m_{best,i} - m_{ji}) \times \beta, \quad (35)$$

$$f_{ji} = f_{ji} + (f_{best,i} - f_{ji}) \times \beta. \quad (36)$$

Otherwise, the individuals undergoing random transitions will be chosen based on the value of the optimization function, as shown in Eqs (35) and (36). Where:

m_j and f_j are the male and female axolotls, respectively;

min_i and max_i are the limits of the variables;

pm_j and pf_j denote the inverse probability of transition for male and female respectively;

om_j and of_j denote the optimization values for male and female populations, respectively;

$u, u_i \in [0,1]$: a random number;

β represents a transition parameter in $[0,1]$;

m_{best} and f_{best} are the best adapted males and females.

Step 6: Injury and restoration phase of axolotls

Axolotls are occasionally prone to accidents and injuries when they enter the water. If the probability of damage is met, the axolotl will lose some body parts. Regeneration is ensured, as indicated in Eq (37).

$$P'_{ji} = min_i + (max_i - min_i) \times u. \quad (37)$$

During this phase, regenerated solutions may violate the non-convex FOR constraints of CHP units. To restore feasibility, we employ an orthogonal projection operator rather than standard techniques such as penalty functions, repair heuristics, or death penalties. Penalty functions require

careful tuning of penalty coefficients and may converge to infeasible solutions due to the non-convex nature of the FOR. Repair heuristics may introduce bias or sacrifice solution quality. Death penalties discard valuable search information. The proposed projection method maps any infeasible point (p_k^{CHP}, H_k^{CHP}) produced by Eq (37) to the nearest feasible point on the FOR-polygon boundary, computed using standard Euclidean projection:

$$\Pi(p_k^{CHP}, H_k^{CHP}) = \operatorname{argmin}_{(P_k, H_k) \in F_k} \|(P_k^{CHP} - P_k, H_k^{CHP} - H_k)\|, \quad (38)$$

where F_k denotes the FOR of CHP unit k , defined as :

$$F_k = \left\{ (P_k, H_k) \in \mathbb{R}^2 : A_k \begin{bmatrix} P_k \\ H_k \end{bmatrix} \leq b_k \right\}$$

$A_k \in \mathbb{R}^{m \times 2}$ and $b_k \in \mathbb{R}^m$ define the m linear constraints of the FOR polygon.

This projection-based approach is computationally efficient for the CHP units, requires no parameters tuning, and guarantees feasibility while preserving the search direction. These properties make it superior to standard constraint-handling techniques in the non-convex context of CHP dispatch.

Step 7: Reproduction and assortment

The male axolotl deposits spermatophores, while the female collects them with her cloaca and places them in her spermatheca. Assume that each pair of axolotls produces two eggs (potential solutions), each containing a blend of genetic information from both parents. The eggs are deposited and are considered hatched for the next stage, the assortment process. Newly generated solutions (larvae) compete with their parent solutions (existing solutions) based on their objective function values. If the young larva performs better, it is placed in the optimal position.

During this phase, a feasibility-first selection criterion is applied:

- ✓ Feasible solutions should always be selected before infeasible solutions.
- ✓ If both the solutions are feasible, then the solution with better objective value will be selected.
- ✓ For CHP units, violations of FOR constraints are repaired by projecting the solution into the closest point from the feasible region using a boundary projection method.

Step 8: Checking the stopping criterion

Repeat Steps 5–7 until the termination criteria of the algorithm is reached, then report the minimum total cost and optimum values of power and heat generation.

One notable feature of MAO is its use of two subpopulations (males and females), which evolve independently during steps 5 and 7. This separation allows MAO to explore different areas of the search space, introducing new information into the subpopulation and reducing the risk of premature convergence to local minimum [79]. Figure 3 illustrates the main steps of the MAO for addressing the hybrid wind-CHPDEED problem.

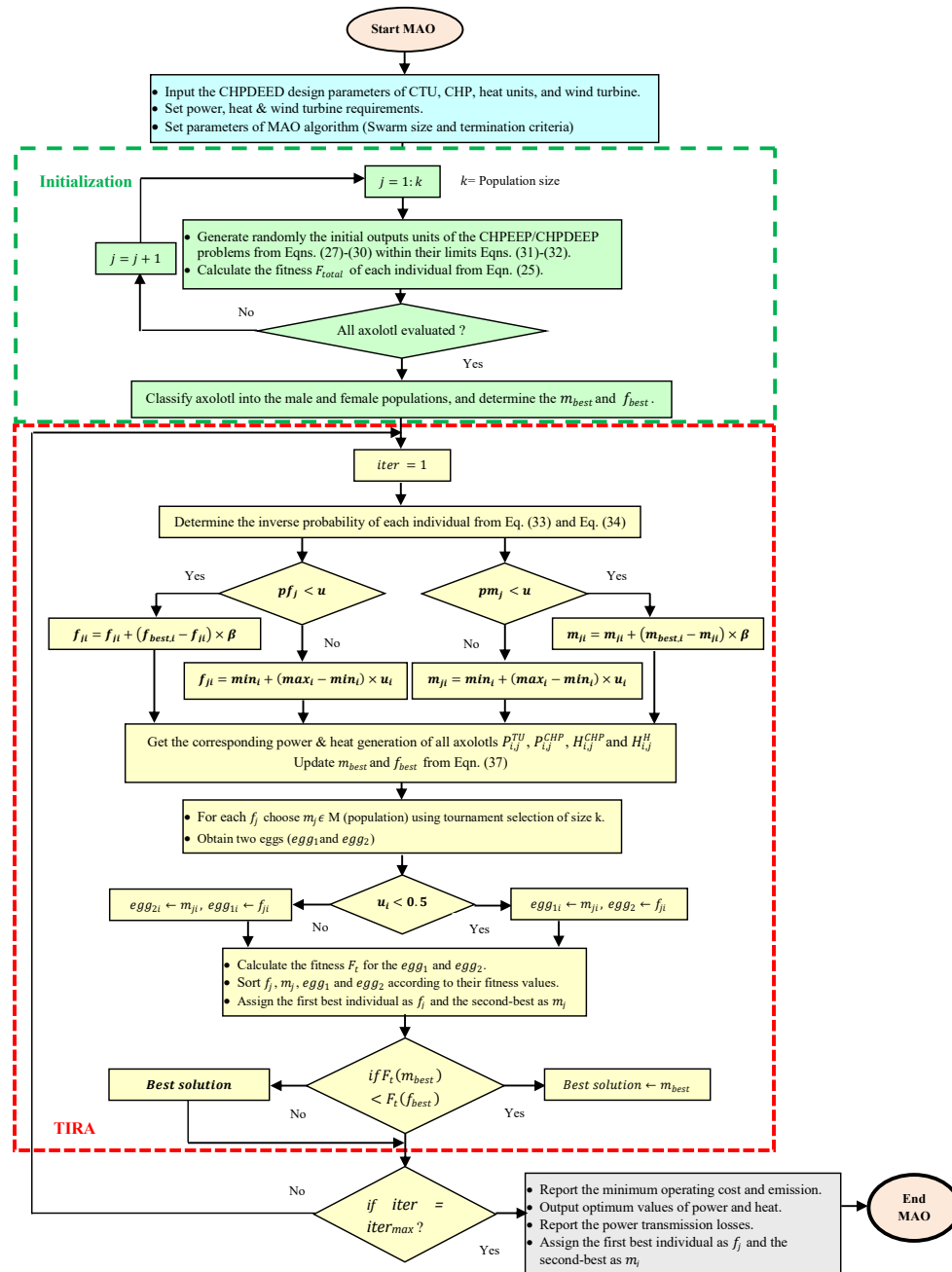


Figure 3. Flowchart of the MAO for the wind-based CHPDEED problem.

4. Results and discussion

To evaluate the effectiveness of our method, we have designed in this section four case studies of CHP problems, ranging from simple to complex, with varying aims. The MAO approach, along with other proposed algorithms like atom search optimization (ASO) [95], time-varying acceleration particle swarm optimization (TACPSO) [96], improved particle swarm optimization (IPSO) [97], and equilibrium optimizer (EO) [98], has been applied to two commonly used test systems in the literature: the 5-unit and 7-unit systems. Cases 1 and 2 apply a static CHP dispatch problem to the 5-unit and 7-unit systems, respectively. Case 3 involves a dynamic dispatch issue applied to the 7-unit system, in

which VPLe, transmission loss, and RRL constraints were considered simultaneously. Case 4 examines the integration of a wind power plant into a 7-unit system to address the CHPDEED issue under the same practical constraints as case 3. Table 1 outlines the specifications of the test systems and case studies applied to solve different types of CHPEED.

Table 1. Specifications of cases and test systems studied for solving CHPEED issues.

Case	Test system	CHPEED type	Model constraints
1	5-unit	Static dispatch	Heat and power demands, capacity limits.
2		Static dispatch	Heat and power demands, capacity limits, VPLe, and transmission loss.
3	7-unit	Dynamic dispatch	Heat and power demands, capacity limits VPLe, transmission loss, and RRL.
4		Dynamic dispatch with integrating wind turbines	Heat and power demands, capacity limits VPLe, and transmission loss, and RRL.

All proposed methods were implemented in MATLAB R2017b and executed on a PC with a 2.7 GHz Intel® Core™ i5 CPU and 16 GB of RAM. The parameter values of MAO algorithm across all cases were consistently set as follows [99]: damage probability(dp) of 0.5, regeneration probability(rp) of 0.1, tournament size (t_{tourn}) of 3, differentiation constant (β) of 0.5, and crossover probability (cop) of 0.5. The parameter values for the ASO, TACPSO, IPSO, and EO algorithms were extracted from references [95–98], respectively.

To provide rigorous statistical evidence for the comparative performance, we performed pairwise Wilcoxon signed-rank tests on the objective function values obtained by MAO against each competing method over 50 independent runs. The significance level was set at $\alpha = 0.05$.

4.1. Case 1

The first case is a static dispatch problem tested on a 5-unit system, which contains one CTU (unit 1), three CHP units (units 2-4), and one heat-only unit (unit 5) [26]. The test system's power and heat demands are set to 300 MW and 150 MWth, respectively. The system's statistics are derived from references [26,50,60]. A detailed description of the technical data used in this test case is provided in Tables A.1 and A.2 (Appendix A). For simplicity, VPLe and transmission power losses are ignored in this case ($P_{loss} = 0$). Three scenarios are examined in this case:

- Scenario I: The objective function only considers the production cost ($w=1$).
- Scenario II: The objective function only considers the gas emission ($w=0$).
- Scenario III: The objective function considers both economic cost minimization and emission reduction CHPEED ($w=0.5$).

4.1.1. Scenario I

Table 2 depicts the optimal planning of heat and power generation, the minimum fuel cost (FC), and the computation time. For comparison, the results obtained using our techniques are compared with those of other recently published methods. Based on the optimal solutions provided in Table 2,

the MFC for the CHPED problem ranges from 13613.00\$ to 14810.8986\$. Clearly, the RCGA-IMM algorithm employed in [100] achieves the lowest fuel cost (FC) at 13613.00 \$. Our MAO technique achieves the minimum operational cost of 13687.2628\$ with a computational time of 3.8320 s. On the other hand, it can be observed that EDHS [101], HSGA [102], and CPSO [15] achieved lower FC values than MAO, but their operating points were not feasible solutions.

Table 2. Optimal solutions obtained for CHPED for scenario I (case 1 when $w=1$).

Output	$P = 300 \text{ MW}$				$H = 150 \text{ MWth}$				Min Cost (\$/h)	Time (s)
	P_1^{CTU}	P_2^{CHP}	P_3^{CHP}	P_4^{CHP}	H_2^{CHP}	H_3^{CHP}	H_4^{CHP}	H_5^H		
Proposed MAO	135.0000	108.0107	39.5179	17.4714	55.7605	55.0000	0.0000	39.2395	13687.2628	3.8320
ASO	119.7725	95.4554	40.2736	44.4985	69.1740	12.4308	30.6962	37.6991	13812.4843	5.2480
TACPSO	81.9876	100.2221	31.4058	86.3845	35.9140	9.5114	44.5746	60.0000	13842.7102	3.8438
IPSO	125.4155	72.1287	59.3185	43.1373	50.5436	55.0000	0.0000	44.4564	13867.8199	3.8750
EO	135.0000	0.0000	60.0000	104.9990	107.2565	0.0000	0.0000	42.7430	14810.8986	19.5894
HSGA ^a [94]	134.8600	23.8400	12.0200	129.2600	74.8800	33.8100	0.3400	40.9700	13611.1500	—
EDHS ^a [93]	135.0000	18.1563	13.0749	133.7688	84.0626	37.7659	0.0000	28.1118	13613.0000	—
RCGA-IMM [92]	135.0000	40.7680	19.2320	105.0000	73.5960	36.7760	0.0000	39.6280	13613.0000	—
CPSO ^a [95]	135.0000	40.7309	19.2728	105.0000	64.4003	26.4119	0.0000	59.1955	13692.5212	—
GSA [47]	135.0000	41.7806	18.1736	105.0000	74.0890	37.3336	0.0000	38.5713	13671.1490	—
EMA [4]	135.0000	40.7163	19.2837	105.0000	73.7022	36.7183	0.0000	39.5829	13672.7407	—
DCWOA [63]	135.0000	40.7591	19.2398	105.0000	73.6165	36.7193	0.00000	39.6645	13672.7969	—
BD [19]	135.0000	40.7687	19.2313	105.0000	73.5957	36.7759	0.0000	39.6284	13672.8300	—
TVAC-PSO [95]	135.0000	41.4019	18.5981	105.0000	73.3562	37.4295	0.0000	39.2143	13672.8892	—
Hybrid NSGA-II and MOPSO [61]	135.0000	40.2760	19.7240	105.0000	72.9971	37.9461	0.0000	39.0568	13673.0000	—
MRFOA [96]	134.9987	41.2774	73.8340	18.7420	35.6649	104.981	0.0291	40.4719	13673.1300	—
EMA [97]	135.0000	40.0751	20.0000	104.9249	73.9673	36.2419	0.0000	39.7908	13673.2982	—
RCGA [57]	134.9904	49.9525	25.0827	89.9744	73.5089	35.8519	1.2916	39.3476	13776.14 00	—
IBEA [61]	134.8000	63.2000	12.5000	90.1000	73.0000	35.5000	9.5000	36.7000	13856.7000	—
IDBEA [61]	132.8000	43.8000	36.3000	87.5000	59.2000	28.4000	3.7000	59.8000	13914.8000	—

^a Not feasible, NA; Not reported.

For the MAO technique, the generation cost exceeds that of GSA [50], EMA [4], DCWOA [66], BD [22], TVAC-PSO [103], hybrid NSGA-II/MPSO [64], and MRFOA [104], and presenting production costs of 13671.1490, 13672.7407, 13672.7969, 13672.8300, 13672.8892, 13673.0000, and 13673.1300, and respectively. Conversely, MAO's optimal FC is lower than that of HS [46], RCGA [60], ASO, TACPSO, IBEA [61], IPSO, IDBEA [61], and EO, which attain operational cost of 13723.2000, 13776.1400, 13812.4843, 13842.7102, 13856.7000, 13867.8199, 13914.8000, and 14810.8986\$, respectively.

Figures 4 and 5 illustrate the convergence of operating costs obtained using the MAO, ASO, TACPSO, IPSO, and EO algorithms. The variations in the MFC solutions obtained from 50 runs using MAO and other methods for scenario I are illustrated in Figure 6, while Figure 7 compares the operating cost values obtained by different approaches, listed in Table 2.

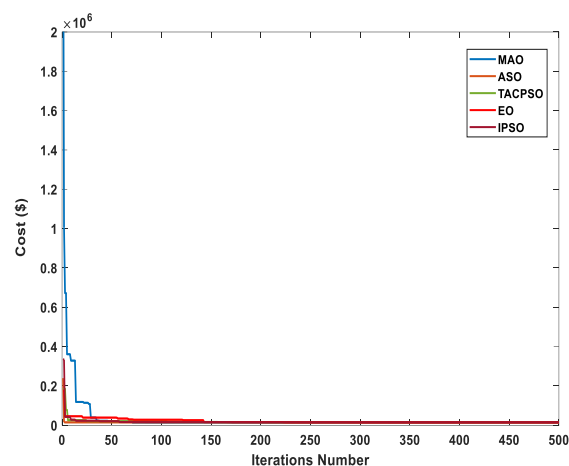


Figure 4. Convergence characteristics of MAO and other methods for the optimal operating cost of scenario I.

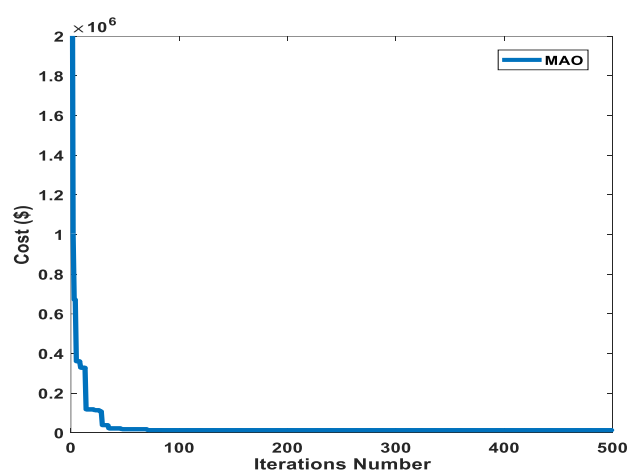


Figure 5. Convergence properties of MAO for 5-unit's system, scenario I.

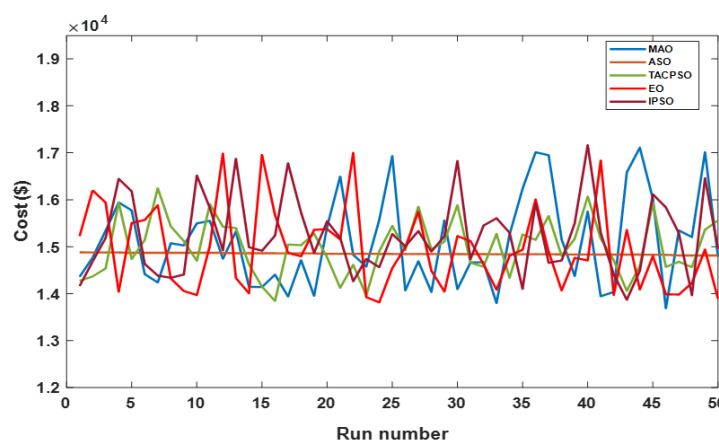


Figure 6. Variations of solutions obtained for 50 runs using MAO and other methods for optimal CHP economic dispatch, scenario I (case 1).

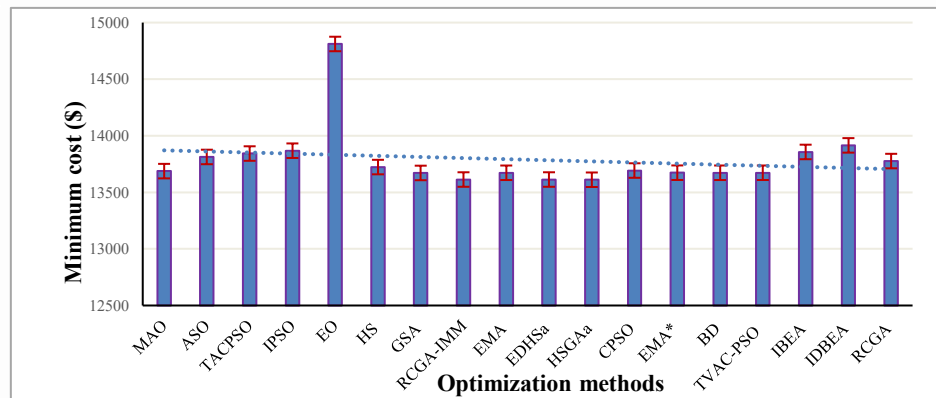


Figure 7. Comparison of operating costs obtained by different methods for scenario I (case 1).

4.1.2. Scenario II

Table 3 compares the optimal solutions obtained using MAO with those obtained using various optimization methods.

Table 3. Optimal solutions obtained for scenario II (CHP environmental dispatch, $w=0$).

Output	$P = 300 \text{ MW}$				$H = 150 \text{ MWth}$				Min Emission (kg/h)	Time (s)
	P_1^{CTU}	P_2^{CHP}	P_3^{CHP}	P_4^{CHP}	H_2^{CHP}	H_3^{CHP}	H_4^{CHP}	H_5^H		
MAO	35.0000	125.8000	49.2210	89.9790	0.0000	75.4745	54.5254	20.0000	1.1914	2.3215
ASO	35.0000	122.6644	52.3367	89.9989	0.0000	75.0000	40.0000	35.0000	1.1931	3.6792
TACPSO	35.0000	125.8000	49.1985	90.0000	0.0000	75.0000	55.0000	20.0000	1.1938	3.1457
IPSO	35.0000	118.9853	59.4250	86.5898	0.2939	75.0000	51.0672	23.6389	1.1994	4.0843
EO	35.0000	125.8000	60.0000	79.2000	0.0000	75.0000	55.0000	20.0000	1.2032	13.8403
DCWOA [67]	34.9998	125.7992	34.2006	104.9993	133.8644	16.1356	0.0000	0.0000	1.1749	—
Hybrid NSGA-II/MOPSO [64]	35.0000	109.4862	53.1560	102.3578	124.3056	23.6797	1.0991	0.9156	1.1883	—
IDBEA [61]	35.3000	116.9000	43.6000	104.6000	90.5000	44.7000	0.3000	16.7000	1.2000	—
IBEA [61]	35.0000	112.4000	52.1000	101.1000	93.8000	20.0000	0.0800	37.8000	1.3000	—
RCGA [60]	39.2000	125.8000	45.0000	90.0000	32.3998	55.0000	24.9999	37.6002	1.4460	—

Table 3 and Figure 8 demonstrate that the minimum emission for scenario II is achieved at 1.1914 kg/h with an average CPU time of 2.3215 s, while maintaining all operational limits. Compared to RCGA [60], IBEA [61], EO, IDBEA [61], IPSO, TACPSO, and ASO algorithms, emission achieved by the MAO method are reduced by 0.2546, 0.1086, 0.0118, 0.0086, 0.008, 0.0024, and 0.0017 kg, respectively. However, the MAO achieves lower emissions than DCWOA [66], and Hybrid NS GA-II/MOPSO [63], with reductions of 0.0191, and 0.0057 kg, respectively.

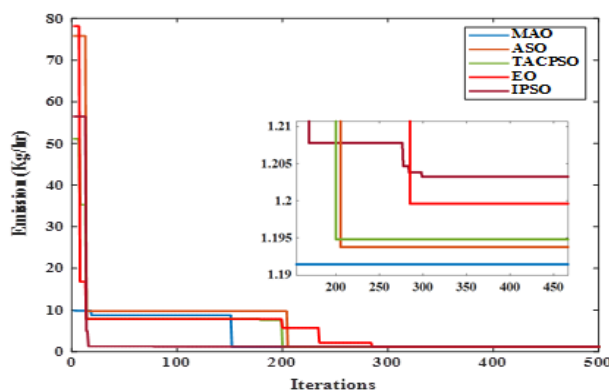


Figure 8. MAO and other methods, convergence for scenario II.

Figure 9 shows the robustness metrics of the MAO algorithm in terms of statistical values. These results are summarized in Table 4 with the corresponding Wilcoxon signed-rank tests. For scenario 1 (economic dispatch), MAO achieves comparable performance to ASO ($p = 0.8624$) and TACPSO ($p = 0.7312$), while significantly outperforming IPSO ($p = 0.0418$). However, MAO outperforms EO with statistical significance ($p = 0.0032$), consistent with EO's markedly higher cost (14810.90 compared to 13687.26 for MAO). In scenario II (environmental dispatch), MAO significantly outperforms all competitors ($p < 0.01$), confirming its superior effectiveness for emission minimization.

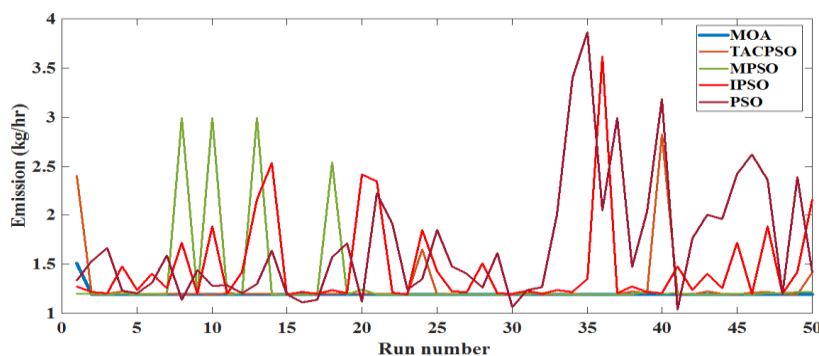


Figure 9. Comparison of emission obtained by different methods for scenario II.

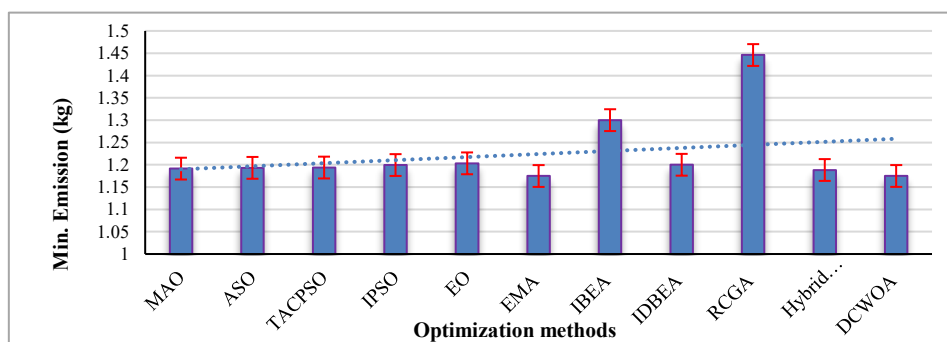


Figure 10. CHP environmental dispatch comparison for scenario II.

Table 4. Optimal schedule of MO-CHPEED and Wilcoxon test results for case 1 (scenarios I and II).

Static dispatch	Outputs	MAO	ASO	TACPSO	IPSO	EO
Optimal CHP Economic Dispatch (\$/h)	Mean	15103.4497	14846.7198	14996.5282	15233.7207	14940.7635
	Min	13687.2628	13812.4843	13842.7102	13867.8199	14810.8986
	Worst	17108.9790	14878.5976	16243.9801	17162.7300	16998.0111
	STD	959.5857	18.0937	583.6456	815.5446	878.8006
	Time (s)	3.8320	5.2480	3.8438	3.8750	19.5894
	Wilcoxon p-value	—	0.8624 [—]	0.7312 [—]	0.0418 ⁺	0.0032 ⁺
Optimal CHP Environmental Dispatch (kg/h)	Mean	1,1974	1.4313	1.4878	1.3452	1.4154
	Min	1.1914	1.1931	1.1938	1.1004	1.2032
	Worst	1.5080	2.8271	2.9910	3.6162	3.8653
	STD	0.0520	0.98119	0.52129	0.51492	0.64069
	Time (s)	2.3215	3.6792	3.1457	4.0843	13.8403
	Wilcoxon p-value	—	0.0091 ⁺	0.0063 ⁺	0.0017 ⁺	0.0004 ⁺

Note: '+' indicates MAO significantly outperforms competitor ($p < 0.05$); '⊥' indicates competitor significantly outperforms MAO ($p < 0.05$); '—' indicates no significant difference ($p \geq 0.05$).

4.1.3. Scenario III

The optimal dispatch provided in Table 5 (Figure 11) demonstrates the ability of the MAO algorithm to minimize both generation costs and emissions while meeting all operational constraints. As shown in Figure 11 and Table 5, minimum costs and emissions are achieved at 14772.0791\$ and 5.4210 kg/h, respectively, with a simulation time of 5.9527 s. compared with MRFOA [104], Hybrid NSGA-II/MOPSO [64], SPEA 2 [60], and NSGA-II [60] algorithms, the MAO reduces production costs by 0.89%, 0.93%, 1.30%, and 1.60%, respectively, while emissions decreased by 8.57%, 8.45%, 17.44%, and 11.71%, respectively. Furthermore, the superiority of our algorithm over other established methods has been demonstrated. Figure 11 shows that costs and emissions cannot be improved further without degrading the other metric.

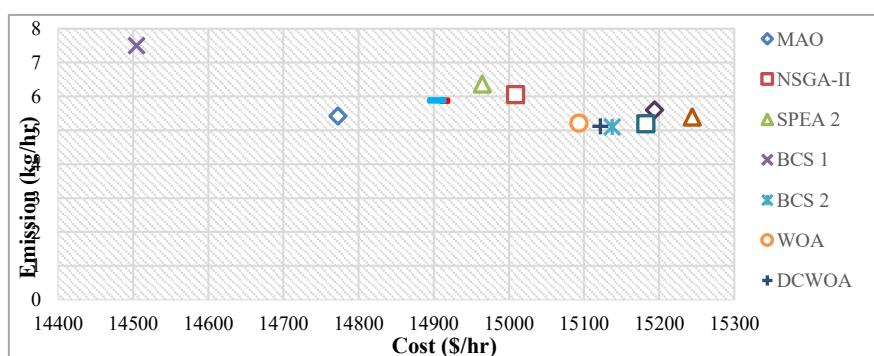


Figure 11. Comparison of the best solution for CHPEED obtained by different methods for scenario III.

Table 5. Optimal schedule of MO-CHPEED for scenario III.

Output	$P = 300 \text{ MW}$				$H = 150 \text{ MWth}$				Cost (\$/h)	Emission (kg/h)	Time (s)
	P_1^{CTU}	P_2^{CHP}	P_3^{CHP}	P_4^{CHP}	H_2^{CHP}	H_3^{CHP}	H_4^{CHP}	H_5^H			
Proposed	88.870	78.68	60.00	72.442	55.00	75.00	0.000	20.000	14772.07		5.9527
MAO	9	59	00	7	00	00	0	0	91	5.4210	
BCS 1[65]	105.60	61.70	27.80	104.90	76.40	39.50	0.005	34.100	14504.20		—
	00	00	00	00	00	00	3	0	00	7.5000	
Hybrid NSGA-II- MOPSO [64]	92.493	70.37	32.19	104.94	81.43	25.59	0.029	42.940	14909.00		—
	0	07	59	04	78	19	7	6	00	5.8794	
SPEA 2[60]	96.484	71.17	44.50	87.843	84.76	10.21	17.90	37.110	14964.30		—
	6	05	18	1	60	86	54	0	00	6.3667	
NSGA-II [60]	93.904	72.82	43.34	89.921	84.92	22.60	2.626	39.844	15008.70		—
	4	98	48	0	50	32	8	9	00	6.0563	
WOA [64]	86.720	74.67	33.67	105.00	75.90	32.59	0.001	41.502	15092.97		—
	8	03	03	00	14	44	7	5	00	5.2188	
DCWOA [66]	85.867	75.05	34.07	105.00	76.94	32.75	0.000	40.300	15121.40		—
	4	65	52	00	99	03	0	3	00	5.1232	
BCS 2 [65]	85.600	80.10	29.30	105.00	76.50	39.30	0.000	34.200	15137.30		—
	0	00	00	00	00	00	4	0	00	5.1000	
IDBEA [61]	87.100	95.50	17.30	100.20	61.40	41.00	0.200	49.000	15182.00		—
	0	00	00	00	00	00	0	0	00	5.2000	
IBEA [61]	90.300	86.90	38.20	84.700	78.30	16.10	11.20	44.800	15193.50		—
	0	00	00	0	00	00	00	0	00	5.6000	
GWO[105]	88.500	94.60	29.00	87.900	54.00	39.90	21.00	35.200	15243.70		—
	0	00	00	0	00	00	00	0	00	5.4000	

4.2. Case 2

To further evaluate the robustness of our method, we applied it to a more complex case. This case involved a static dispatch problem in a 7-unit system consisting of 4 CTU units (1-4), 2 CHP units (5-6), and 1 heat-only unit (7) [26]. The load and heat demands were set at 600 MW and 150 MWth, respectively. The data for this system was obtained from [26,61,64]. The data for the fuel cost functions with VPLE and the emission functions are provided in Appendix B (Tables B.1 and B.2). The B matrix transmission loss coefficients are available in [59]. To verify the effectiveness of the MAO technique, case 2 simultaneously considers the VPLE and transmission losses, unlike Case 1.

Table 6 presents the optimal power and heat dispatch results obtained for some weighting factors, along with production costs, gas emissions, and power losses. Under the cost-minimization criterion, our algorithm demonstrated a significant cost reduction, achieving a total cost of 9938.9267 \$. It represents cost savings of 172.3133, 239.5044, 353.3733, 479.7733, and 773.9333\$ compared with GWO [105], TVAC-PSO [59], IDBEA [61], IBEA [61], and RCGA [60] methodologies, respectively, with a power transmission loss of 6.5600 MW. Figure 12 shows the convergence characteristic graph of the optimal CHP economic dispatch for case 2 over iterations.

Table 6. Comparison of optimal CHPD issues obtained by different techniques for case 2.

Static dispatch	Outputs	MAO	GWO [105]	TVAC-PSO [59]	IDBEA [61]	IBEA [61]	RCGA [60]
Optimal CHP	P_1^{CTU} (MW)	64.5308	52.8074	60.7435	65.7000	68.6000	74.5357
	P_2^{CTU}	98.5398	98.5398	92.5941	97.3000	92.8000	99.3518
	P_3^{CTU}	112.6734	112.6735	108.6744	112.4000	113.5000	174.7196
	P_4^{CTU}	209.8158	209.8158	205.6843	209.2000	206.2000	211.0170
	P_5^{CHP}	81.0000	93.8115	92.8127	83.3000	84.6000	100.9363
	Economic H_5^{CHP} (MWth)	0.0000	29.3704	35.2512	93.9000	91.7000	24.3678
	Dispatch P_6^{CHP}	40.0000	40.0000	40.1326	40.3000	42.3000	44.1036
	($w = 1$) H_6^{CHP}	93.5441	75.0000	73.0402	59.8000	55.2000	72.5270
	H_7^H	56.4591	29.3704	41.7086	0.2000	5.6000	53.1052
	Cost	9938.9267	10111.24	10178.4311	10292.3000	10418.7000	10712.86
	P_L	6.5600	7.6499	NR	6.7000	6.7000	NR
	Outputs	MAO	IBEA [61]	IDBEA [61]	GWO [105]	RCGA [60]	TVAC-PSO [59]
Optimal CHP	P_1^{CTU} (MW)	42.6939	42.1000	43.4000	47.2117	73.3318	75
	P_2^{CTU}	49.2180	59.0000	38.2000	60.5702	81.0489	116.3409
	P_3^{CTU}	60.8811	63.2000	63.9000	65.9821	93.4210	120.9164
	P_4^{CTU}	82.1264	79.8000	98.8000	79.3252	125.2112	164.7382
	P_5^{CHP}	247	246.3000	246.1000	244.4299	214.9958	81.9903
	Environmental H_5^{CHP} (MWth)	85.4481	106.3000	105.6000	14.4000	104.7715	98.9693
	Dispatch P_6^{CHP}	125.8000	116.1000	116.0000	110.2000	125.7907	41.6528
	($w = 0$) H_6^{CHP}	64.5519	52.8000	47.9000	135.6000	31.9272	50.5794
	H_7^H	0.0000	0.0000	3.4000	0.0000	13.3013	0.45128
	Emission	7.0383	7.6000	7.7000	8.1088	16.9208	49.423
	P_L	7.8210	6.4000	6.4000	7.7100	NR	NR
	Outputs	MAO	GWO [105]	IDBEA [61]	IBEA [61]	NSGA-II [60]	SPEA 2 [60]
Optimal CHP	P_1^{CTU} (MW)	55.6141	68.7669	64.5000	61.6000	73.5896	73.3149
	P_2^{CTU}	75.5540	98.4445	95.8000	100.4000	106.8761	117.7996
	P_3^{CTU}	114.1763	98.5285	95.5000	103.8000	119.0311	117.7996
	P_4^{CTU}	127.8527	109.8509	122.0000	119.3000	163.5563	151.6436
	P_5^{CHP}	193.9815	192.0000	188.6000	157.9000	188.4166	195.1355
	Economic H_5^{CHP} (MWth)	97.7304	5.6924	92.5000	88.6000	26.8054	25.8784
	Environmental P_6^{CHP}	40.0000	40.0000	40.2000	63.2000	58.4850	54.0988
	Dispatch H_6^{CHP}	14.2658	75.0000	57.0000	70.8000	73.9970	75.5331
	($w=0.5$) H_7^H	38.0309	69.3076	1.6000	4.2000	49.1976	48.5884
	Cost	12181.2687	12402.90	12957.2000	13029.5000	13433.19	13448.95
	Emission	16.9626	17.4093	17.3000	18.1000	25.8262	25.7810
	P_L	7.4783	7.5840	6.1000	6.1000	NR	NR

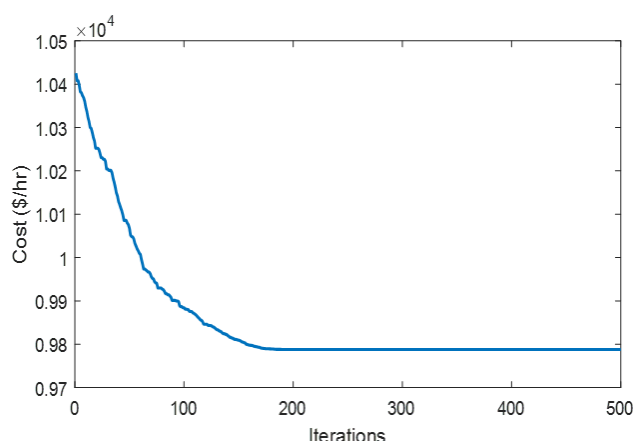


Figure 12. Convergence characteristics of MAO for optimal costs for case 2.

With regard to emission reduction, the optimal solutions of the CHPMD problem for 7-unit systems range from 7.0383 to 49.423 kg. The reduction in optimal emissions of the proposed MAO was 7.98%, 9.40%, 15.21%, 140.41%, and 602.20%, when compared with IBEA [61], IDBEA [61], GWO [105], RCGA [60], and TVAC-PSO [59] approaches, respectively. Power transmission losses were 7.8210 MW. Figure 13 illustrates the convergence behavior of our proposed method for optimizing CHP environmental dispatch in Case 2. Compared to GWO [105], IDBEA [61], IBEA [61], NSGA-II [60], and SPEA 2 [60] techniques, the MAO method was more effective in minimizing both operating costs and emissions reduction. Our approach achieved a total cost of 12181.2687\$, an emission reduction of 16.9626 kg, and transmission losses of 7.4783 MW, with all operational limits satisfied.

Table 7 illustrates the statistical analysis and Wilcoxon test results for the different CHPD values obtained in case 2. MAO consistently outperforms the other methods across the economic, emission, and combined economic-environmental dispatch problems for cogeneration-based systems, with significant superiority over all competitors in all scenarios ($p < 0.05$), confirming its robustness on more complex problems involving both VPLE and transmission losses.

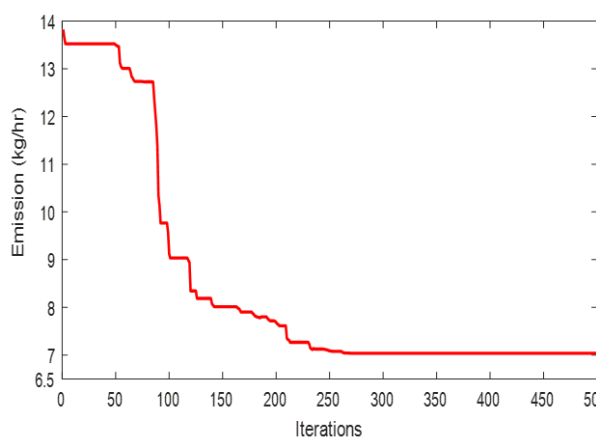


Figure 13. Convergence behavior of MAO for optimal emissions for case 2.

Table 7. Statistical analysis and Wilcoxon test results for Case 2 (7-unit system).

CHP problems	Method	Min	Average	Max	STD	Wilcoxon p-value
Optimal CHP Economic Dispatch (\$/h) ($w = 1$)	MAO	9938.9267	10053.7392	10143.0573	92.3105	—
	GWO [105]	10111.2400	10245.8320	10324.5610	115.4320	0.0412 ⁺
	TVAC-PSO [59]	10178.4311	10309.2670	10398.1240	120.9870	0.0387 ⁺
	IDBEA [61]	10292.3000	10424.5680	10513.7890	128.4560	0.0234 ⁺
	IBEA [61]	10418.7000	10552.8900	10641.2340	135.6720	0.0112 ⁺
	RCGA [60]	10712.8600	10849.1230	10943.5670	142.8310	0.0019 ⁺
Optimal CHP Environmental Dispatch (kg/h) ($w = 0$)	MAO	7.0383	7.3481	7.9869	0.8304	—
	IBEA [61]	7.6000	7.8500	8.2340	0.6780	0.0065 ⁺
	IDBEA [61]	7.7000	7.9430	8.5670	0.7340	0.0041 ⁺
	GWO [105]	8.1088	8.3420	8.7890	0.8120	0.0012 ⁺
	RCGA [60]	16.9208	17.2134	17.8456	1.2340	0.0001 ⁺
	TVAC-PSO [59]	49.4230	50.1234	51.2345	2.3450	0.0001 ⁺
Optimal CHPDEED (Obj. Function) ($w = 0.5$)	MAO	6099.1156	6114.3892	6192.5847	43.5521	—
	GWO [105]	6343.8000	6378.9200	6456.3400	51.2340	0.0237 ⁺
	IDBEA [61]	6435.5600	6467.8900	6543.2100	58.7560	0.0098 ⁺
	IBEA [61]	6483.7400	6512.4500	6598.7600	62.3210	0.0061 ⁺
	NSGA-II [60]	6667.8300	6712.4500	6798.7600	68.4320	0.0003 ⁺
	SPEA 2 [60]	6684.2300	6723.8900	6812.3400	71.2340	0.0002 ⁺

4.3. Case 3

In contrast to the static dispatch used in previous cases, this study employs dynamic dispatch for a 7-unit system. The system includes VLPE and transmission line losses and considers both economic and environmental objectives with the same weighting coefficient ($w=0.5$). To meet the system's demand, the time horizon was divided into 24 hourly intervals. This period accommodates daily load variations, including peak and off-peak intervals, enabling realistic operational planning. Table 8 presents the test system's hourly load and heat demand profiles [91]. Different load profiles can significantly affect optimal solutions. For instance, peak demand necessitates different generation strategies than those used during off-peak periods. While daily load profiles can be used, they may underestimate operational costs and gas emissions. Monthly-adjusted typical daily load profiles offer improved accuracy, but the most precise optimization requires real load data [106].

Table 9 presents the optimal generation schedules obtained using the MAO method for the CHPDEED problem. The table also provides the corresponding total cost, emissions, and power transmission losses for each time interval. The proposed technique achieved total costs, total emissions, and total losses of 234 128.9503\$, 584.1166 kg, and 155.4763 MW, respectively.

Figures 14 and 15 depict the optimal generation schedules for minimizing both costs and emissions. Figure 14 demonstrates, that during the peak electrical load period, CTU and CHP units generate more electricity to meet system demand. In contrast, Figure 15 shows that CHP units and heat-only units primarily satisfy heat load demand, especially at night, when it is high, while it is lower during the day.

Table 8. Hourly demand, heat demand, and wind power output.

Time (h)	Demand (MW)	Heat Demand (MWth)	Wind Power Output (MW)	Time (h)	Demand (MW)	Heat Demand (MWth)	Wind Power Output (MW)
1	447.000	160.000	7.56	13	534.000	125.280	10.42
2	438.000	163.200	7.5	14	528.000	124.800	10.15
3	423.000	165.120	8.25	15	528.000	124.960	9.67
4	408.000	166.400	8.48	16	525.000	125.760	8.98
5	450.000	163.200	8.48	17	522.000	127.360	8.37
6	492.000	160.000	9.42	18	534.000	129.600	7.61
7	588.000	152.000	9.82	19	690.000	134.400	6.7
8	612.000	144.000	10.35	20	780.000	140.800	5.72
9	618.000	137.600	10.88	21	740.000	147.200	7.21
10	588.000	132.800	11.01	22	714.000	153.600	7.75
11	558.000	129.600	10.94	23	624.000	158.400	7.88
12	540.000	126.720	10.68	24	456.000	160.000	7.69

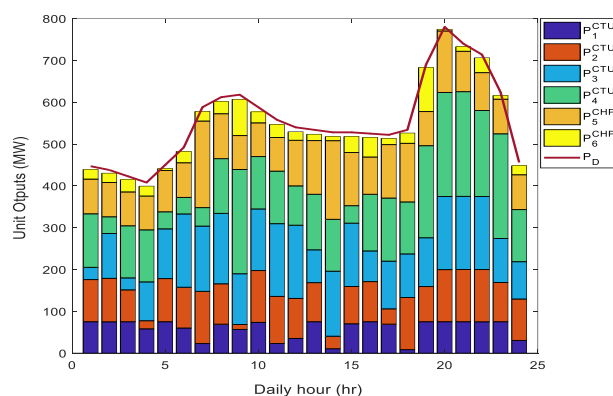


Figure 14. Optimal power schedule found by MAO for case 3.

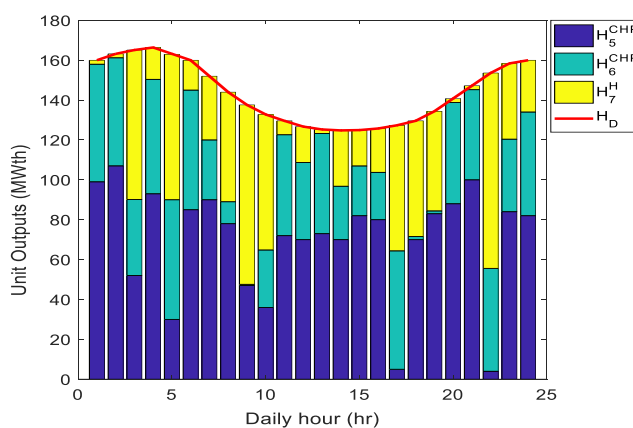


Figure 15. Best heat dispatch found by MAO for case 3.

Table 9. Hourly power schedule and heat obtained for the CHPDEED problem for case 3.

Time (h)	Conventional power units				CHP units		Heat units		
	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5		Unit 6		Unit 7
	P_1^{CTU}	P_2^{CTU}	P_3^{CTU}	P_4^{CTU}	P_5^{CHP}	H_5^{CHP}	P_6^{CHP}	H_6^{CHP}	H_7^H
1	75.0000	100.8079	29.5059	127.7109	83.0842	99.0000	23.3310	59.0000	2.0000
2	74.8200	104.1262	107.3194	39.6169	82.0755	107.0000	22.5446	54.2000	2.0000
3	75.0000	76.1788	28.6456	124.5293	80.9996	52.0000	29.3967	38.1200	75.0000
4	57.9974	19.3463	92.9210	124.3723	80.9598	93.0000	23.9253	57.4000	16.0000
5	75.0000	103.1670	118.8220	40.8077	98.8171	30.0000	4.9062	60.0000	73.0000
6	59.9919	97.7310	175.0000	39.7735	82.5577	85.0000	27.5258	60.0000	15.0000
7	22.9246	125.0000	155.8108	44.0498	207.1086	90.0000	23.2862	30.0000	32.0000
8	69.3737	96.2794	168.6867	130.4650	107.4648	78.0000	29.3841	11.0000	55.0000
9	56.9023	11.7322	121.0388	249.4465	80.9955	47.0000	87.0043	0.6000	90.0000
10	73.7490	123.6348	147.2633	125.3197	80.5264	36.0000	26.4967	28.8000	68.0000
11	23.2480	112.6294	173.4906	125.8124	80.4573	72.0000	31.4190	50.6000	7.0000
12	35.4127	95.5619	175.0000	93.7977	109.2895	70.0000	20.2581	38.7200	18.0000
13	75.0000	93.4125	78.4831	133.0876	128.1208	73.0000	15.4761	50.2800	2.0000
14	10.3756	30.2399	155.4091	124.0700	187.7220	70.0000	10.0381	26.8000	28.0000
15	70.0924	89.3800	151.3527	41.5506	127.5989	82.0000	38.3524	24.9600	18.0000
16	75.0000	95.9365	73.3183	135.7434	88.8547	80.0000	47.1672	23.7600	22.0000
17	69.4047	36.3934	114.1727	150.7802	127.7168	5.0000	15.1583	59.3600	63.0000
18	8.2408	125.0000	103.8906	124.3015	140.4074	70.0000	24.5497	1.6000	58.0000
19	75.0000	84.1623	116.5910	220.0822	81.7367	83.0000	105.7278	1.4000	50.0000
20	75.0000	124.5699	175.0000	248.8991	146.7047	88.0000	4.1138	50.8000	2.0000
21	75.0000	125.0000	175.0000	250.0000	96.8573	100.0000	10.9327	45.2000	2.0000
22	74.8286	125.0000	174.8660	205.6201	90.1878	4.0000	35.7476	51.6000	98.0000
23	75.0000	94.0330	105.2127	250.0000	82.9999	84.0000	8.8669	36.4000	38.0000
24	30.5787	98.8040	89.1031	124.6908	83.1920	82.0000	21.9407	52.0000	26.0000

4.4. Case 4

The case studied is similar to case 3 but includes wind power plants as RES. The wind turbine's hourly output power is provided in Table 8. This study prioritized both cost minimization and emissions reduction ($w=0.5$) during the integration of a wind turbine. Table 10 displays the optimal results for the hybrid wind-CHPDEED problem obtained using our MAO technique. Figures 16 and 17 illustrate the hourly power and heat generation schedules optimized by the MAO approach. Figure 16 shows that the wind turbine generates electricity continuously throughout the scheduling period. The load is low at night, while the heat load and wind power are high.

Table 10. Hourly power flow schedule and heat obtained for case 4.

Time (h)	Conventional power units				CHP units				Heat units
	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5		Unit 6		Unit 7
	P_1^{CTU}	P_2^{CTU}	P_3^{CTU}	P_4^{CTU}	P_5^{CHP}	H_5^{CHP}	P_6^{CHP}	H_6^{CHP}	H_7^H
1	59.8147	23.5909	111.0414	120.0545	83.1446	20.00000	53.22461	80.00000	60.00000
2	55.0145	100.4024	85.1342	56.7837	96.0384	75.00000	48.80812	40.00000	48.20000
3	49.7276	93.8599	34.3301	119.1495	83.0330	5.00000	46.65197	100.0000	60.00000
4	75.0000	44.5424	66.5503	94.1905	84.9480	55.00000	45.99816	58.00000	53.40000
5	70.9424	99.9279	110.8180	45.4459	84.0077	5.00000	43.00188	105.0000	53.20000
6	34.6060	96.0258	111.0019	124.6806	85.0537	50.00000	45.42967	100.0000	10.00000
7	59.5513	118.3700	139.7883	124.9989	96.0605	20.00000	56.09102	80.00000	52.00000
8	66.5921	99.9703	116.0880	205.4262	84.9997	70.00000	46.39556	42.00000	32.00000
9	68.7960	120.4060	134.9843	103.4069	135.9284	50.00000	61.98521	58.00000	29.60000
10	67.0473	86.0520	101.5065	204.7266	86.1957	75.00000	49.37677	28.00000	29.80000
11	45.2351	79.5571	55.9837	245.9843	85.2073	50.00000	52.97286	25.00000	54.60000
12	71.8914	100.7594	110.4633	124.2707	84.3747	5.00000	53.96669	80.00000	41.72000
13	44.5479	88.2548	44.2174	116.1184	200.7326	25.00000	46.00958	95.00000	5.28000
14	75.0000	67.9905	107.9613	129.4428	86.9736	35.00000	66.04005	48.00000	41.80000
15	34.1619	94.6955	74.0838	167.6630	102.7224	45.00000	59.47390	62.00000	17.96000
16	65.2252	97.2932	112.2340	124.0301	83.9374	5.00000	47.65211	78.00000	42.76000
17	36.3688	115.1407	120.6093	42.7484	146.4066	100.00000	66.18027	12.00000	15.36000
18	54.7390	33.0828	136.5003	155.6461	109.8162	80.00000	49.14914	12.00000	37.60000
19	74.1989	110.9685	130.9389	158.0178	175.6125	20.00000	49.73027	95.00000	19.40000
20	73.4807	125.0765	175.8015	247.1509	119.6648	5.00000	51.30891	88.00000	47.80000
21	74.9217	120.2558	172.5725	247.3897	83.7391	5.00000	52.29733	90.00000	52.20000
22	75.0000	106.5419	173.5063	184.0078	137.2089	65.00000	47.63656	72.00000	16.60000
23	63.8566	116.6007	115.2857	208.1788	84.1091	5.00000	43.97522	98.00000	55.40000
24	50.1004	99.4050	59.7774	125.9026	86.4666	32.00000	38.54462	70.00000	58.00000

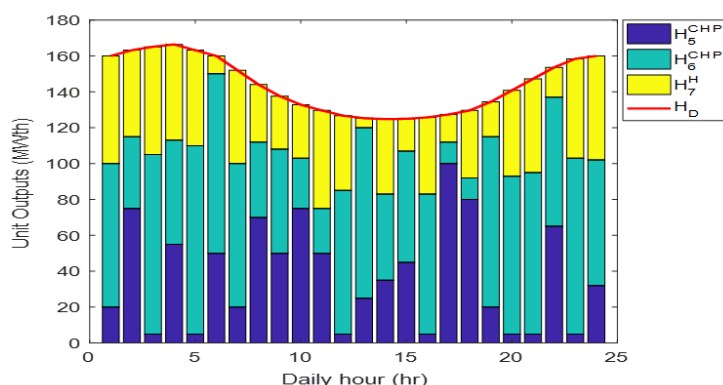


Figure 16. Optimal power schedule found by MAO for case 4 when $w=0.5$.

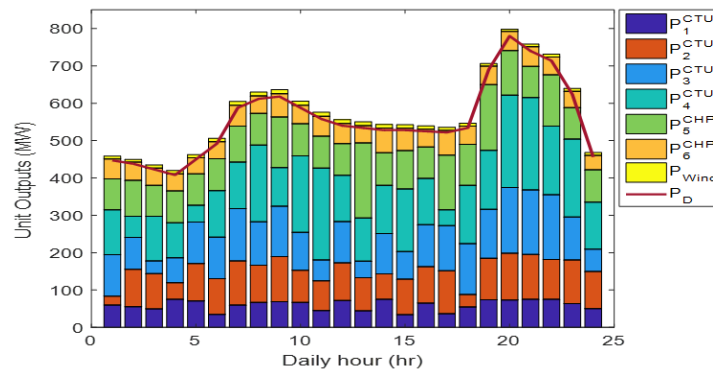


Figure 17. Best heat dispatch found by MAO for case 4 when $w=0.5$.

Figure 18 illustrates the impact of integrating a wind generator on power losses at different time intervals. At certain times, transmission line losses in the grid, including those associated with wind power plants, may exceed those of a system without a wind turbine. It can be attributed to several factors, including power quality problems, reactive power flow, operational considerations, and grid integration challenges. Integrating wind energy into the load profile significantly improves the system's ability to adapt to changing demand patterns.

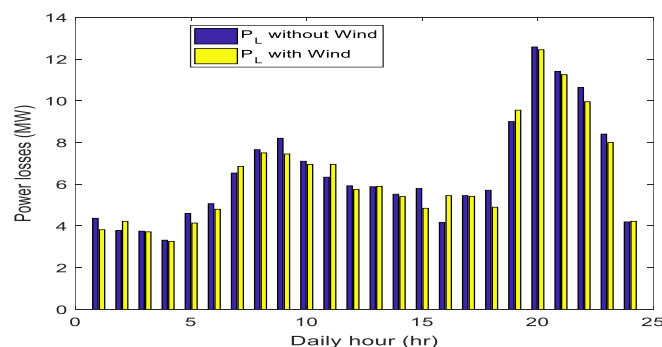


Figure 18. Comparison of hourly power losses with and without wind farm integration.

Table 11 compares the costs, emissions, and transmission-line losses without and with integration of a wind turbine using the MAO approach. Incorporating wind turbines into CHPDEED problems leads to different optimal solutions compared with the scenario without wind energy. The 24-hour simulation of the MAO algorithm showed a reduced total cost of 227269.9546\$ per hour and reduced carbon emissions of 551.0357 kg per hour when wind turbines were integrated. This compares favorably with a cost of 234 128.9503\$ per hour and emissions of 584.1166 kg per hour, without wind integration. The addition of RRL increased both total the cost and emissions compared to the unconstrained case, as expected, due to the incapacity of generating units to rapidly change their output. Despite RRL, wind integration (case 4) still yields a 2.93% cost reduction, 5.66% emission reduction and 1.70% reduction in transmission losses compared with the optimal results without wind turbine (case 3).

Table 12 compares total system operating costs between case 3 and case 4 across three demand

regimes, using hourly cost data. These results demonstrate that the wind system yields economic benefits during peak demand, making it a useful resource for system operators to manage high-demand conditions efficiently.

Table 11. Hourly comparison of cost, emissions, and losses resulting from the CHPDEED issue with and without integrated wind turbines.

Time (h)	Case 3 (Without Wind)			Case 4 (With Wind)		
	Cost (\$)	Emission (kg)	Loss (MW)	Cost (\$)	Emission (kg)	Loss (MW)
1	8351.5196	15.2525	4.3707	8350.8926	14.5022	3.8211
2	8416.6221	15.0658	3.7813	9900.2154	12.1142	4.2245
3	8795.1375	12.8643	3.7520	8300.3654	12.8325	3.7203
4	8460.5703	11.3153	3.3201	8850.1125	10.2547	3.2574
5	8910.4074	15.6377	4.6048	8380.9824	15.6003	4.1411
6	8616.8353	23.9932	5.0676	8830.1068	17.5411	4.8021
7	11738.7080	23.2913	6.5401	9200.0752	25.7366	6.8574
8	9679.9708	29.4686	7.6619	9050.8402	29.4981	7.5056
9	11612.4784	31.2364	8.2069	10400.6511	24.8004	7.4538
10	9204.0088	28.2382	7.1049	9130.2511	26.9042	6.9541
11	8659.1897	28.6458	6.3404	9020.6621	28.3447	6.9555
12	9266.0705	24.3109	5.9261	8400.4195	20.8552	5.7478
13	9396.5147	17.4150	5.8806	11630.0032	11.3035	5.9003
14	10639.4684	16.5816	5.5244	9150.1365	18.2417	5.4114
15	10767.7742	18.0361	5.8005	9630.4109	18.5982	4.8502
16	9995.5966	17.5166	4.1720	8390.3479	19.5502	5.4548
17	9610.0046	18.0970	5.4540	11570.4150	15.9541	5.4217
18	10664.5564	18.4217	5.7135	9900.2751	20.1554	4.9001
19	13135.8766	28.7558	9.0068	11330.1288	27.6065	9.5532
20	10338.3560	49.2923	12.5833	10220.9844	49.3352	12.4505
21	9582.4104	49.1385	11.4162	9360.5512	48.9599	11.2552
22	10433.5197	42.9053	10.6456	10860.6504	36.6047	9.9590
23	9304.7736	33,7243	8.4060	8850.3044	31.4534	8.0047
24	8548.5807	14.9124	4.1966	8560.1725	14.2887	4.2252
Total	234 128.9503	584.1166	155.4763	227269.9546	551.0357	152.8270

Table 12. Period-based cost comparison of objective functions for cases 3 and 4.

Period	Metric	Case 3	Case 4	Improvement (%)
Low-Demand Period (Hours 1-6, 24)	Average Hourly Cost	8585.6675	8738.9782	-1.79%
	Total Cost (7 hours)	60099.6729	61172.8476	-1.79%
Medium- Demand Period (Hours 7-18, 22-23)	Average Hourly Cost	10069.4739	9656.1030	4.11%
	Total Cost (14 hours)	140972.6344	135185.4426	4.11%
Peak- Demand Period (Hours 19-21)	Average Hourly Cost	11018.8810	10303.8881	6.49%
	Total Cost (3 hours)	33056.6430	30911.6644	6.49%

Table 13 displays a detailed numerical comparison of the Wilcoxon p-value, minimum, average, and maximum total costs (Obj Function) before and after wind energy system insertion. Results in case 4 (with Wind) significantly outperform the without-wind case, achieving reductions of 2.94%, 3.37%, and 2.5% for the minimum, average, and maximum total costs, respectively. These enhancements are statistically significant at the 5% level ($p < 0.001$ for all metrics), which proves that wind system installation makes cost savings consistent and significant in the CHPDEED issue. The collective results shown in Tables 9–13, along with the visualizations in Figures 14–18, validate the performance of our MAO approach in solving the hybrid wind-CHPDEED problem.

Table 13. Statistical analysis and Wilcoxon test results for dynamic dispatch (Cases 3 and 4).

Outputs	Without Wind	With Wind	Improvement %	Wilcoxon p-value	Significance
Minimum	117356.5335	113910.4952	2.9364	<0.001	+
Average	117936.0291	113967.1338	3.3653	<0.001	+
Maximum	118014.6247	115482.3195	2.1457	<0.001	+

Although case study 4 confirms the potential economic and environmental advantages of wind integration under idealized deterministic conditions, these benefits may be compromised in real-world operations due to the inherent uncertainty of wind power forecasts. This uncertainty, driven by the stochastic nature of meteorological conditions and the limitations of current predictive models, poses significant challenges for system operators. Accurate and reliable wind forecasting [107] is therefore a prerequisite for maintaining a stable energy supply, ensuring grid stability, reducing operating costs, and maximizing economic returns in competitive energy markets.

5. Conclusions

This paper demonstrates the application of the Mexican Axolotl Optimization (MAO) algorithm to solve combined heat and power dispatch (CHPD) problems, with or without a wind turbine integrated into the power system, while maintaining all operating constraints. Two test systems, 5- and 7-unit systems with varying complexity levels, were used to evaluate the algorithm's robustness in handling different CHPD challenges: static economic environmental dispatch, dynamic economic environmental dispatch, and hybrid wind-CHP dynamic economic environmental dispatch. A weighting method was employed to convert the MO-CHPD economic emission dispatch (MO-CHPDEED) problem into a single-objective optimization problem. The key findings of this research are summarized below:

- **For the 5-unit test system:**

The optimal static economic dispatch for the CHP in case study 1, without considering VPLE and power losses, was 13687.2628\$, with a computational time of 3.8320 s (Table 2). The corresponding optimal static emission was 1.1914 kg/h, with an average simulation time of 2.3215 s (Table 3).

- **For the 7-unit test system:**

For the 7-unit system, when considering both VPLE and power losses (case 2), the best static economic dispatch cost for CHP was 9938.9267 \$, with transmission line losses of 6.5600 MW. The corresponding minimum emission was reduced to 7.0383 kg. Power transmission losses were 7.8210 MW. As shown in Table 6, the optimal solution for both cost and emissions was obtained at a total

cost of 12181.2687\$ and emissions of 16.9626 kg, with transmission losses of 7.4783 MW. Both wind-integrated and conventional scenarios satisfied all generator operating constraints and system electrical demand, yielding operating points clustered along the perimeter of the feasible operating region.

For CHPDEED without integrating a wind generator (case 3), the best total costs and emissions were 234,128.9503 \$ and 584.1166 kg, respectively. The total power losses were 155.4763 MW. When a wind power plant was integrated into the CHPDEED problem (case 4), the optimal total costs and total emissions were reduced to 227,269.9546 \$ and 551.0357 kg, respectively. This represents a cost reduction of 2.93% and an emissions reduction of 5.66% compared with the system without wind. Additionally, total losses decreased by 1.70%. MAO with wind significantly outperforms that without wind ($p < 0.05$, Wilcoxon signed-rank test, 50 independent runs).

Across all case studies, MAO consistently outperformed other techniques, demonstrating its effectiveness and robustness in handling diverse and complex CHPD problems.

6. Limitations of the study and future work

- MAO, like many optimization methods, may face significant computational challenges, particularly when addressing complex problems with large solution spaces. This complexity can lead to longer processing times, which could restrict its applicability in real-time scenarios or large-scale optimization tasks.
- The MAO algorithm's performance is highly sensitive to its parameter settings. To address this, future research will focus on experimentally evaluating each phase of the method to determine optimal parameter values, aiming to improve both speed and solution quality, particularly for complex optimization problems. This will provide practical guidelines to the scientific community for selecting MAO parameters.
- The MO-CHPDEED problem has no single optimal solution satisfying all objectives simultaneously; rather, multiple Pareto-optimal solutions exist. Additionally, we plan to employ novel Pareto-based approaches to address these challenges by taking into account energy storage, wind-power forecasting, and other renewable energy units.
- Renewable generation uncertainty will be incorporated into MO-CHP dispatch optimization through stochastic optimization and robust optimization frameworks.
- We will apply the MAO algorithm to minimize the total cycle cost of an IES that combines power, hydrogen, and heat cogeneration (CPHH-IES).

Author contributions

Benyekhlef Larouci: Data curation, Validation, Supervision, Resources, Writing–review and editing, Project administration, Funding acquisition; Houari Boudjella: Supervision, Conceptualization, validation, Investigation, Writing–review and editing; Khaled Guerraiche: Methodology, Software, Formal analysis, Investigation, Visualization, Writing–original draft; Latifa Dekhici: Conceptualization, Validation, Investigation, Writing–review and editing; Aykut Fatih Güven: Supervision, Formal analysis, Validation, Writing–review and editing, Visualization; Abdul Wadood: Methodology, Formal analysis, Validation, Writing–review and editing; Herie Park: Supervision, Validation, Resources, Writing–review and editing; Byung O. Kang: Conceptualization, Supervision,

Validation, Project administration, Writing–review and editing. All authors have read and approved the final version of the manuscript for publication.

Use of Generative-AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declared no conflicts of interest.

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Appendix A

Table A.1. Cost function parameters of 5-unit test system [26].

Power only units							
Unit	a (\$)	b (\$/MW)	c (\$/MW ²)	h (\$/MW ³)	P_{min} (MW)	P_{max} (MW)	
1	254.8863	7.6997	0.00172	0.000115	35	135	
CHP units							
	a (\$)	b (\$/MW)	c (\$/MW ²)	d (\$/MWth ²)	e (\$/MWth)	f (\$/(MW·MWth))	
						Feasible region coordinates [P^c, H^c]	
2	1250	36.00	0.0435	0.600	0.027	0.011	[44, 0], [44, 15.9], [40, 75], [110.2, 135.6], [125.8, 32.4], [125.8, 0]
3	2650	34.50	0.1035	2.203	0.025	0.051	[20, 0], [10, 40], [45, 55], [60, 0]
4	1565	20.00	0.072	2.300	0.020	0.040	[35, 0], [35, 20], [90, 45], [90, 25], [105, 0]
Heat only units							
	a (\$)	b (\$/MWth)	c (\$/MWth ²)	H_{min}^h (MWth)	H_{max}^h (MWth)		
7	950	2.0109	0.038	0	60		

Table A.2. Emission function parameters of 5-unit test system [26].

Power only units					
Unit	α	β	γ	η	δ
1	4.091×10^{-4}	-5.554×10^{-4}	6.490×10^{-4}	2.00×10^{-4}	0.02857
CHP units					
2	$E_{c2}(P_2, H_2) = 0.00165\ P_2\ kg$				
3	$E_{c3}(P_3, H_3) = 0.0022\ P_3\ kg$				
4	$E_{c4}(P_4, H_4) = 0.0011\ P_4\ kg$				
Heat only units					
5	$E_{h5}(H_5) = 0.0017\ H_5\ kg$				

Appendix B

Table B.1. Cost function parameters of 7-unit test system C.

Power only units								
Unit	a (\$)	b (\$/MW)	c (\$/MW ²)	e (\$)	f (rad/MW)	P_{min} (MW)	P_{max} (MW)	$DR_I^{CTU} = UR_I^{CTU}$
1	25	2	0.008	100	0.042	10	75	30
2	60	1.8	0.003	140	0.040	20	20	25
3	100	2.1	0.0012	160	0.038	30	175	40
4	120	2	0.001	180	0.037	40	250	50
CHP units								
	a (\$)	b (\$/MW)	c (\$/MW ²)	d (\$/MWth)	e (\$/MWth ²)	f (\$/(MW.MWth))	Feasible region coordinates [P^c , H^c]	$DR_k^{CHP} = UR_k^{CHP}$ (MW/h)
5	265 0	14.5	0.0345	4.2	0.03	0.031	[98.8, 0], [81, 104.8], [215, 180], [247, 0]	30
6	125 0	36	0.0435	0.6	0.027	0.011	[44, 0], [44, 15.9], [40, 75], [110.2, 135.6], [125.8, 32.4], [125.8, 0]	25
Heat only units								
	a (\$)	b (\$/MWth)	c (\$/MWth ²)	H_{min}^h (MWth)	H_{max}^h (MWth)			
7	950	2.0109	0.038	0	2695.2			

Table B.2. Emission function parameters of 7-unit test system [26,61].

Power only units					
Unit	α	β	γ	η	δ
1	4.091×10^{-4}	-5.554×10^{-4}	6.490×10^{-4}	2.00×10^{-4}	0.02857
2	2.543×10^{-4}	-6.047×10^{-4}	5.638×10^{-4}	5.00×10^{-4}	0.03333
3	4.258×10^{-4}	-5.094×10^{-4}	4.586×10^{-4}	1.00×10^{-6}	0.0800
4	5.326×10^{-4}	-3.550×10^{-4}	3.370×10^{-4}	2.00×10^{-3}	0.0200
CHP units					
5	$E_{c5}(P_5, H_5) = 0.00165\ P_5\ \ kg$				
6	$E_{c6}(P_6, H_6) = 0.00165\ P_6\ \ kg$				
Heat only units					
7	$E_{h7}(H_7) = 0.0018\ H_7\ \ kg$				

The 7-unit system B-matrix (in units of 1/MW) is expressed as follows [23,58]:

$$B = 10^{-7} \times \begin{bmatrix} 25 & 20 & 15 & 15 & 14 & 49 \\ 19 & 18 & 20 & 16 & 45 & 14 \\ 15 & 12 & 10 & 39 & 16 & 15 \\ 11 & 14 & 40 & 10 & 20 & 15 \\ 17 & 35 & 14 & 12 & 18 & 20 \\ 39 & 17 & 11 & 15 & 19 & 25 \end{bmatrix}.$$



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