applied sciences

MDPI

Article

Analysis of Heuristic Optimization Technique Solutions for Combined Heat-Power Economic Load Dispatch

Nagendra Singh [1,*], Tulika Chakrabarti [2], Prasun Chakrabarti [3], Vladimir Panchenko [4], Dmitry Budnikov [5], Igor Yudaev [6] and Vadim Bolshev [5,*]

1 Department of Electrical Engineering, Trinity College of Engineering and Technology, Karimnagar 505001, Telangana, India
2 Department of Chemistry, Sir Padampat Singhania University, Udaipur 313601, Rajasthan, India; tulika.chakrabarti@spsu.ac.in
3 Department of Computer Science and Engineering, Sir Padampat Singhania University, Udaipur 313601, Rajasthan, India; drprasun.cse@gmail.com
4 Department of Theoretical and Applied Mechanics, Russian University of Transport, 127994 Moscow, Russia; pancheska@mail.ru
5 Federal Scientific Agroengineering Center VIM, 109428 Moscow, Russia; dimm13@inbox.ru
6 Energy Department, Kuban State Agrarian University, 350044 Krasnodar, Russia; etsh1965@mail.ru
* Correspondence: nsingh007@rediffmail.com (N.S.); vadimbolshev@gmail.com (V.B.); Tel.: +7-499-174-8595 (V.B.)

Abstract: Thermal power plants use coal as a fuel to create electricity while wasting a significant amount of energy as heat. If the heat and power plants are combined and used in cogeneration systems, it is possible to reuse the waste heat and hence enhance the overall efficiency of the power plant. In order to minimize production costs while taking system constraints into account, it is important to find out the optimal operating point of power and heat for each unit. Combined heat and power production is now widely used to improve thermal efficiency, lower environmental emissions, and reduce power generation costs. In order to determine the best solutions to the combined heat and power economic dispatch problem, several traditional as well as innovative heuristic optimization approaches were employed. This study offers a thorough analysis of the use of heuristic optimization techniques for the solution of the combined heat and power economic dispatch problem. In this proposed work, the most well-known heuristic optimization methods are examined and used for the solution of various generating unit systems, such as 4, 7, 11, 24, 48, 84, and 96, taking into account various constraints. This study analyzes how various evolutionary approaches are performed for various test systems. The heuristic methodologies' best outcomes for various case studies with restrictions are contrasted.

Keywords: heuristic optimization techniques; combined heat-power economic dispatch (CHPED); constraints; environmental emission

check for updates

Citation: Singh, N.; Chakrabarti, T.; Chakrabarti, P.; Panchenko, V.; Budnikov, D.; Yudaev, I.; Bolshev, V. Analysis of Heuristic Optimization Technique Solutions for Combined Heat-Power Economic Load Dispatch. *Appl. Sci.* **2023**, *13*, 10380. https://doi.org/10.3390/app131810380

Academic Editor: Alberto Benato

Received: 9 August 2023
Revised: 13 September 2023
Accepted: 15 September 2023
Published: 16 September 2023

1. Introduction

Major worries about a number of causes, most notably climate change, the scarcity of oil and its consequent rise in price, population levels, and energy consumption, are rapidly dominating the world's energy supply and demand landscape. Finding a substitute for fossil fuels, especially petroleum fuels, is therefore crucial from an economic, environmental, and social standpoint [1].

Primary fossil fuels are converted somewhat inefficiently into electricity. The conventional generating plant achieves efficiencies of 50% to 60% only, because most of the heat energy is wasted during the conversion process and discharged into the environment [2]. Cogeneration, also known as combined heat and power (CHP) generation, is an advanced and modern technology that outperforms conventional energy conversion systems and is also environmentally friendly [3].

CHP systems are systems that simultaneously provide consumers with electricity and meet heating demands [4]. A tri-generation system (cooling, heating, and power generation) can be created by integrating thermally activated technologies into the CHP system to fulfill the consumer's cooling requirement [5]. CHP systems can enhance the efficiencies of thermal power plants by over 90% and decrease their environmental effects [6].

CHP systems get more attention because they can enhance the economics and sustainability of electrical generating units [7]. CHP economic dispatch can improve the efficiency of the energy conversion process in thermal power stations and reduce the cost of power generation [8]. CHP units have the capacity to generate electricity from a range of fuels while simultaneously recovering and reusing the heat that would typically be lost during the creation of electricity [9].

Moreover, the use of CHP generation systems decreases pollutant emissions, such asCOx, SOx, and NOx [10–15]. Because of these factors, researchers have focused increasingly on CHP units in recent years in an effort to fully explore their potential for meeting consumer demands for heat and electricity [16,17]. The economic dispatch (ED) issue, which may be seen as the researchers' initial attempt to maximize the advantages of power systems, tries to determine the best scheduling of the generation units to reduce the fuel cost of power generation subject to operational and technological restrictions [18,19]. The combined economic dispatch problem not only offers significant economic power generation advantages but also lessens the negative consequences of polluting gases [20–22]. During studies in this area of research, it was found that many available articles showed the effectiveness of heuristic optimization for the solution of combined heat and power economic dispatch (CHPED), but no one had demonstrated a complete comparative study between all the proposed heuristic approaches in this research area. Due to this research gap, the authors of this article were motivated to conduct this study.

The objective of this research is to investigate the best heuristic optimization techniques used to address the nonconvex and non-smooth CHPED optimization issues. The bulk of the articles that used heuristic optimization techniques to find the optimum solution to the CHPED issue are discussed in this proposed article, to the best knowledge of the authors. To familiarize readers with the heuristic approaches used, a brief explanation of the utilized heuristic methods is given, and the most important contributions of each research work are introduced. Additionally, in order to create a helpful survey on the usage of heuristic approaches for the solution of the CHPED issue, the best solutions found in the articles under consideration are tallied. There are comparisons between the publications that have been examined in terms of objective function, restrictions, minimal operational cost, and computing time. This article will be of great use to scholars looking at the best generation planning for CHP systems. The rest of the document is structured as follows: Section 2 provides reviews of several heuristic optimization methods that have been applied to the CHPED issue in distinct case studies. The CHPED problem formulation is shown in Section 3. A thorough review of heuristic optimization techniques, handling various constraints and benefits of the heuristic techniques, are shown in Section 4. Comparative results in terms of cost generation and computation time taken in convergence by various optimization techniques are shown in Section 5, and the proposed work's conclusion is given in Section 6.

2. Literature Review

Researchers have been interested in the CHP economic dispatch problem recently, and the answer has been found in earlier literature utilizing a variety of conventional and modern heuristic methods. In the early 1990s, research started in the field of CHP problems and suggested a quadratic programming method for the solution of this problem for 15 generating unit systems [1]. The Lagrangian relaxation technique was proposed for the solution to the CPH problem. They considered one case study for four generating units with load balance and power generation limits [2].

A classical method called Benders decomposition is used for the solution in cases of four and five generating units with two and three co-generation systems with inequality constraints [3]. To obtain optimum results, the four generating units (two co-generation and one heat unit) were optimized by improved PSO (SPSO) for the load demand of 200 MW and the heat demand of 115 MWth [4]. A novel bee colony optimization algorithm [5] and AI (artificial immune) systems [6] were suggested for the study of a 4-generating unit system of CHPED for the load demand of 600 MW and 150 MWth.

Similarly, the firefly algorithm was used for the optimization of CHED for the four generating units, where units 2 and 3 have co-generation and unit 4 has heat. The proposed optimization is used to obtain the global results of power and heat demand of 200 MW and 115 MWth, respectively [7]. For the test data of single heat area and power area systems with loads and heat demands of 200 MW and 115 MWth, respectively, MADS-PSO and, for various power and heat demands, MADS-DACE and MADS-DACE were used [8].

For the solution of nonlinear CHPED, they suggested and demonstrated the effectiveness of TVAC-PSO. The proposed technique was tested on two case study data sets. In the first test case, they considered a four-unit system for the power and heat demand of 200 MW and 115 MWth, respectively. In the second case, they considered a five-unit system for three different load conditions [9].

For the optimization of a large unit data set of CHPED along with constraints, criss-cross optimization was used, and it was found that the proposed techniques gave a global solution for such a large data set. They solved six different cases, and in all cases, the proposed techniques gave the best-optimized solutions compared to the other algorithms [10]. Five different cases of CHPED were considered and global solutions were obtained using the exchange market algorithm. This algorithm was tested for different loads in different data sets (small and large data), and it was found that it gave the global solution in all considered test data [11].

Based on the behavior of humpback whales, the WOA optimization used for the solution of CHPED considered test cases of 24, 84, and 96 data points. The WOA performs well for non-convex nonlinear optimization problems [12]. A crossover and mutation-based improved GA was given for the solution to the CHPED problems [13].

For the non-linear combination of heat and power dispatch systems, the AMPSO algorithm was proposed. To improve the efficiency of the proposed technique, the Taguchi approach was used [14]. A hybrid algorithm is suggested by article [15] for solving the CHP economic emission dispatch problem in such a way as to reduce the cost of generation and emission. Similarly, a deep study discusses the different optimization techniques recommended by the researchers for the solution of the CHP economic emission dispatch problem in article [16].

The CHP economic dispatch problem was solved using the HBOA optimization algorithm, which is based on the interaction of coworkers and employees [17]. A combination of HBA and JSA, commonly known as HBJSA, was used for the solution of the CHP economic load dispatch. The proposed methods overcame the problems associated with HBA and JSA, easily handled the constraints, and solved the nonlinear CHP problem [18]. For the solution to nonlinear CHP, the economic dispatch group search method was suggested, which is based on opposition [19]. The foundation of GSA is the gravitational law, which helps particles move in the search space used to solve CHPED [20].

To solve the CHPED problem with various constraints, biogeography-based particle swarm optimization was suggested. In this PSO, particles update their position by using the migration operator [21]. Based on the cuckoo bird's reproduction behavior, CSA techniques were proposed for the CHPED with a valve-point loading problem solution [22]. The CPH problem was solved using a hybrid approach that combined PPS and CSO for local and global search, respectively [23]. Article [24] demonstrates the use of the group search optimizer for CHP dispatch problems. However, a hybrid (TVAC-GSA-PSO) method was used to solve the large-scale, complex CHPED problems [25]. One more hybrid method (bat algorithm + artificial bee colony) with a chaotic-based self-adaptive search strategy known as CSA-BA-ABC was suggested in article [26] to solve the large-scale, non-differential CHP economic dispatch.

The suggested FS technique in Article [27] was used to solve the CHP economic dispatch in such a way that the cost should be low and fulfill the constraints. Optimization techniques based on the Kho-Kho game (a game played between two teams) were proposed for the CHPED problem [28]. The CHPED problem was solved for a large data system (48 units) with a minimum total operation cost [29]. To minimize the overall fuel cost of cogeneration units, an improved marine predator optimization algorithm was used [30].

For the solution to the CHP dispatch problem with valve-point loading effects and prohibited operating zones, a wavelet-mutated slime mold technique was used [31]. For the purpose of calculating the system-wide additional costs associated with optimum dispatch using the search optimization approach, an explicit formula was created [32]. For the operation of CHP, a demand response algorithm was used [33]. The heat transfer search technique, which follows the laws of thermodynamics and heat transfer, was used to find the solution to complicated CHP economic dispatch problems [34].

To address the CHP dynamic economic dispatch, a new differential evolution method that has an attractive component and gives mutant vectors more possibilities to find prospective locations utilizing migrating variables was proposed [35]. The TVAC-PSO was suggested to address the multi-objective CHPEED and dynamic economic emission dispatch challenges in the context of operational limitations [36].

It was suggested to combine particle swarm optimization algorithms with enthusiasm-aided teaching and learning-based optimization algorithms to simultaneously reduce overall generation costs while taking constraints into account [37]. For handling a very large CHPED (140 bus system), an article proposed a multiobjective technique that was based on a chaotic opposition-based strategy [38]. The usefulness of the group search method in solving the CHPED issue was reported in an article [39].

For the CHPED problem, a genetic algorithm method was suggested [40]. An efficient tool called the search algorithm was proposed to solve the CHPED with ramp rate constraints [41]. The authors of [42] suggested a cuckoo optimization algorithm to solve the CHP in such a way that energy production costs are minimized. In order to solve the CHPED problem, a paper proposed an IDE approach that makes use of mutation operators, dynamical crossover, and population randomization [43].

To solve CHP dispatch problems with bounded and feasible operating regions, researchers used a TLBO approach. In this method, an opposition-based learning approach was incorporated so that convergence speed was enhanced and the simulation results were improved [44].

Grey wolf optimization techniques were used for the solution of CHPD. The effectiveness of the proposed algorithm was tested on the data of 4, 7, 11, and 24 units [45].To reduce the generation cost and environmental emissions, a multiobjective fuzzy-operated system was proposed for the CHPED problem [46]. For the optimization of the power economic dispatch problem along with valve loading and multiple fuel constraints, an improved genetic algorithm approach was proposed. The proposed algorithm was a combination of an improved genetic algorithm and multiplier updating [47].

Using penalty and binary concepts, researchers discussed a cuckoo algorithm for the optimized CHPED problem [48]. A Mühlenbein mutation-based coded genetic algorithm was presented for the solution of the CHP economic dispatch problem. Such mutations enhance the convergence process and improve the results [49]. A multi-player harmony search technique was recommended for the resolution of a non-linear large-scale CHPED issue. The proposed methods were evaluated using data from CHPED 24- and 84-unit systems [50]. An MPSO with a Gaussian random variable was suggested for the optimization of the CHPED problem. The proposed technique had good convergence speed and gave a global solution to the problem [51]. Other authors created a new cuckoo search with elitist CSA to address the issue of CHP economic load dispatch [52]. The CHPED problem was suggested to be solved using improved particle swarm optimization in Article [53].

3. Problem Formulation of CHPED

Thermal generating units, cogeneration units, and heat-only units were taken into consideration for the problem formulation of the CHPED. The heat-power viable operation zone of a combined cycle cogeneration unit is depicted in Figure 1. The KLMNOP boundary curve encloses the viable operation zone.

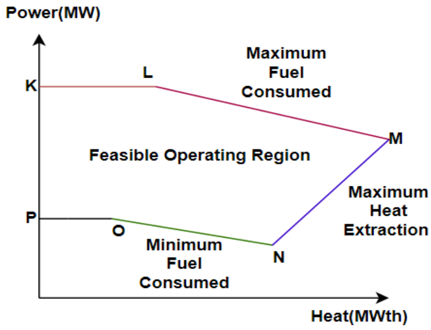

Figure 1. Feasible operating region for a co-generation system.

The heat capacity rises along the boundary curve LM as the generation of electricity falls, whereas it falls along the curve MN. It is obvious that the unit's maximum output power is reached along the KL curve. On the other hand, the MN curve is where the unit produces the most heat.

The main goal of the issue is to estimate the heat and power generation rates for each unit in order to minimize the cost of heat and power generation while meeting the heat and power demands. The CHP load dispatch problem is represented mathematically as follows:

$$min\left(\sum_{i=1}^{N_P} C_i(P_i^P) + \sum_{j=1}^{N_c} C_j(P_j^c, H_j^c) + \sum_{k=1}^{N_h} C_k(H_k^h)\right) \tag{1}$$

where $C_i(P_i^P)$ is total generation cost, $C_j(P_j^c, H_j^c)$ is generation cost with CHP units, and $C_k(H_k^h)$ is generation cost using heat-only units. Np, Nc, and C_k denote the number of power only units, CHP units, and heat only units, respectively. Similarly, i, j and k show the number of power-only units, CHP units, and heat-only units.

The quadratic cost function of power-only units is given as

$$C_i(P_i^p) = a_i(P_i^p)^2 + b_i P_i^p + c_i \tag{2}$$

where $C_i(P_i^p)$ denotes fuel cost of the i^{th} generating units, and a_i, b_i, and c_i are the cost coefficients of power-only units.

A combined heat-power cogeneration system is given as

$$C_j(P_j^c,\ H_j^c) = a_j(P_j^c)^2 + b_j P_j^c + c_j + d_j(H_j^c)^2 + e_j H_j^c + f_j P_j^c H_j^c \tag{3}$$

And a heat-only unit is defined as

$$C_k(H_k^c) = a_k(H_k^h)^2 + b_k H_k^h + c_k \tag{4}$$

3.1. Problem Formulation with Valve-Point Effects

In traditional thermal power plants, a large number of steam valves are utilized to increase turbine speed when the load is high. The plant's cost function is altered as a result of opening the valve in this way. A sinusoidal element is added to the quadratic cost function of traditional thermal units to simulate valve-point consequences. The valve-point effect is taken into account, which creates a non-convex optimization issue. The cost function for power-producing units under the influence of valve loading is expressed as

$$C_i(P_i^p) = a_i(P_i^p)^2 + b_iP_i^p + c_i + \left|d_i sin(e_i(P_i^{min} - p_i^p))\right| \quad (5)$$

where a_i, b_i, and c_i are the fuel coefficients, and d_i and e_i are the valve-loading coefficients.

3.2. Constraints

When power is generated at thermal power plants, it faces many limitations called constraints. The following constraints are considered when the CHP problem is formulated:

3.2.1. Power Balance

Generated power must be equal to the load demand plus the loss of power in the transmission line. It is defined as follows:

$$\sum_{i=1}^{N_p} P_i^p + \sum_{j=1}^{N_h} P_j^p = P_d + P_{Loss} \quad (6)$$

where P_i^p is the power generated by the i$^{\text{th}}$ generating units, and P_d and P_{Loss} are the demand of power and power loss in the transmission line, respectively. Power loss in the transmission line is given as

$$P_{Loss} = \int_{i=1}^{N_p}\int_{l=1}^{N_p} P_i^p B_{il} P_l^p + \int_{i=1}^{N_p}\int_{j=1}^{N_c} P_i^p B_{ij} P_j^c + \int_{j=1}^{N_c}\int_{m=1}^{N_c} P_j^p B_{jm} P_m^c \quad (7)$$

where B_{il}, B_{ij}, and B_{jm} are the line loss coefficients.

3.2.2. Heat Balance

The production of heat is always equal to the demand for heat, called the heat balance, and it is formulated as follows:

$$\sum_{j=1}^{N_c} H_j + \sum_{k=1}^{N_h} H_k = H_d \quad (8)$$

where H_j is the heat generated due to the co-generation system, H_k is the heat generated due to the heat-only unit, and H_d is the head demand.

3.2.3. Generation Limit Due to Power-Only Units

All generating units have limitations between maximum and minimum power generation, as given below.

$$P_i^{p.min} \le P_i^p \le P_i^{p.max} \quad (9)$$

where $P_i^{p.min}$ and $P_i^{p.max}$ are the limits of minimum and maximum power generation.

3.2.4. Capacity Limits of Power and Heat Due to Combined Heat-Power Units Only

$$P_j^{c,min}(H_j) \le P_j^{c,max} \le P_j^c(H_j) \quad (10)$$

$$H_j^{min} \le H_j \le H_j^{max} \quad (11)$$

4. Heuristic Optimization Techniques Analysis

The numerous demands make it difficult to include cogeneration units in the economic dispatch of the power system. The cogeneration units' mutual dependence on each other's heat-power capacity makes it difficult to economically dispatch cogeneration units into the power grid due to the numerous demands (for both heat and electricity). Researchers have put forth a variety of heuristic methods for optimizing the CHPED problem. The many heuristic methods proposed for CHPED optimization are shown in Table 1.

Table 1. Different optimization approaches used for the solution of the CHPED problem.

Ref. No.	Optimization Techniques	Constraints	Taken Case Study for Optimization	Advantages and Disadvantages
[1] 1994	Quadratic programming	Generation limits	15 traditional power units, 9 boilers, and 15 co-generation units	Fast response and does not depend on the size of the data
[2] 1996	Lagrangian relaxation	Power balance and generation limits	7-unit system	Best suitable for small generating unit system optimization
[3] 2013	Benders decomposition	Inequality constraint	4- and 5-unit systems	Performing well for a small data set
[4] 2009	SPSO	Equality and inequality	4 units	Best performing for small test data
[5] 2011	Bee colony	Generation limits	4 units	Fast and effective
[6] 2012	Artificial immune system	Power balance and generation limits	4 units	Gives an optimum solution and takes less CPU time, but does not test the big test data set.
[7] 2013	Firefly algorithm	Power balance and generation limits	4 units	Simple and effective
[8] 2011	Mesh adaptive direct search	Power balance and generation limits	Single- as well as multi-heat area and power area systems	Conceptually, it is very straightforward, easily implementable, and computationally effective.
[9] 2015	TVAC-PSO	Valve point, generation limit, power balance, and heat balance	4- and 84-unit system	Effective for CHPED issues that are non-convex and non-linear
[10] 2015	Crisscross optimization	Valve point, transmission losses, and prohibited operating zones	4,7, 24, and 48units	Effective for large test data also
[11] 2016	Exchange market	Valve-point loss along with power balance and generation limits	4,5, 7, 24, and 48units	Powerful and robust algorithm
[12] 2017	WOA	Valve-point effect, generation limits	24, 84, and 96 units	Easily handles large test data and gives a global solution
[13] 2019	IGA-NCM	Power balance	4-, 5-, 7-, 24- and 48-unit system	It can handle small and large data and give optimal solutions easily.
[14] 2019	Advanced modified PSO	Valve-point effect, power balance, and generation limits	4- and 7-unit system	The suggested technique can locate the ideal solution and avoid local minima.

Table 1. *Cont.*

Ref. No.	Optimization Techniques	Constraints	Taken Case Study for Optimization	Advantages and Disadvantages
[15] 2020	Hybrid NSGA II-MOPSO	Power balance and generation limits	4- and 7-unit system	It can handle single- as well as multi-objective problems.
[17] 2021	HBOA	Transmission losses and the valve point	4, 24, 84, and 96 generating units	Compared to other optimization techniques, the feasibility, capability, and efficiency are better for large-scale systems.
[18] 2021	HBJSA	Power balance and generation limits	24-, 48-, 84- and 96-unit systems	The method used by HBJSA to calculate the lowest minimum, average, and maximum generation costs is very stable and efficient.
[19] 2015	Opposition-based group search	Valve-point loading and prohibited operating zones	4-, 7-, 24-, and 28-unit systems	Best situated for small and large data sets to solve nonlinear problems
[20] 2016	Gravitational search algorithm(GSA)	Valve-point effect, power balance, and generation limits	5-, 7-, 24- and 48-unit systems	Ability to solve large data sets of CHPED problems, good convergence characteristics, and efficiency in computation
[21] 2020	BLPSO	Power and heat limitations and prohibited operating zones.	5, 7, 24, and 48 units	This approach prevents premature convergence and increases the precision of the solution.
[22] 2106	Cuckoo search algorithm (CSA)	Valve point, power losses, and power balance	4 and 5 units	Controls parameters in such a way that they evaluate the high-quality solution and take less computational time.
[23] 2017	CPSO	Prohibited operating zones, valve point, and transmission losses	4, 7, and 24 units	Enhances the quality of the answer while requiring fewer function evaluations.
[24] 2017	MGSO	power balance and valve point	5-, 24-, 48-, 72-, and 96-unit test system	The suggested approach provides a better solution and outperforms existing methods computationally.
[25] 2017	Hybrid TVAC-GSA-PSO	Power balance and generation limits	24 units, 48 units,	This technology is robust in evaluating the minimum generation cost with less expensive solutions.
[26] 2018	CSA-BA-ABC	Power and heat balance and prohibited operation zones	5- and 7-unit test system	Delivering a high-quality solution with more economic benefits and no convergence issues
[27] 2020	SFS	Power balance and generation limits	5- and 7-unit test system	It is possible to avoid local minima and require less computing time.
[28] 2020	Kho-Kho optimization (KKO)	Power balance and prohibited operation zones	5- and 7-unit test system	This method imitates the special technique the chasing squad used to touch the runners team.

Table 1. *Cont.*

Ref. No.	Optimization Techniques	Constraints	Taken Case Study for Optimization	Advantages and Disadvantages
[29] 2020	OQNLP	Valve-point loading effect and power balance	48-unit system	This technique provides an effective tool for dealing with optimization problems.
[30] 2022	Improved marine predators optimization algorithm	Power balance and generation limits	5, 48, 84, 96 units	Convergence characteristics of IMPOA are stable, and computation is also fast.
[31] 2023	Comprehensive learning wavelet-mutated slime mold algorithm	Valve loading, prohibited operating zones, and generation limits	24-, 48-, 84- and 96-unit system	The suggested technique solves the local search issue of population concentration.
[32] 2020	Direct Optimization algorithm	Power balance and generation limits	4-unit system	Good convergence characteristics are suitable for small test data sets.
[33] 2022	C-PSO	Power balance and generation limits	7 units (period of 24 h)	Performs well, and results show it is effective compared to other optimization techniques used for the same test data set.
[34] 2020	Heat transfer search (HTS)	Transmission loss, valve point, and prohibited operating zones	7, 24, and 48 units	Stable operation and less computation time
[35] 2022	Differential evolution	Power generation limits, heat limits, prohibited operating zone	11, 33 and 165 units	This method can hasten the removal of constraint violations and the decrease in the value of the goal function for each solution.
[36] 2019	TVAC-PSO	Prohibited operating zones, spinning reserve, valve point, power loss, and ramp rate	5, 7, and 48 units	It can handle the various constraints and gives a global solution for the considered case.
[37] 2022	ETLBO with IPSO	Valve effects, prohibited operating zones, and power transmission loss	4, 24, and 48 units	Handles constraints easily
[38] 2020	Multi-verse optimization algorithm	Valve point, transmission losses, and ramp limits	4-, 7-, 10-, and 40-unit system	The exceedingly challenging combined economic emission dispatch is solved by the suggested method.
[39] 2016	Group search optimization	Prohibited operating zones and valve-point loading	4, 7, and 24 units	Effective for multiobjective nonlinear problem solutions
[41] 2013	SALCSSA	Ramp rate	10, 30, 150 units (for 24 h)	Gives an optimum solution with a good convergence speed
[42] 2017	Cuckoo optimization algorithm	Valve-point effects	7, 24, 48	Handles the loading effect and gives optimum results.
[43] 2016	IDE	Valve-point effects	13, 38 units	Easily handles the equality constraints

Table 1. *Cont.*

Ref. No.	Optimization Techniques	Constraints	Taken Case Study for Optimization	Advantages and Disadvantages
[44] 2014	Teaching–learning-based optimization	Valve-point loading	7, 24, and 48 units	For multiobjective problems, this approach effectively enhances the overall performance of the solutions.
[45] 2016	Grey wolf optimization	Ramp rate, valve point, and spinning reserve	4, 7, 11, and 24 units	The recommended method works more consistently and with higher-quality solutions.
[46] 2013	Fuzzy logic	Ramp-rate limits	7 units	This technique has the potential to solve a larger, multi-objective problem.
[47] 2005	IGA-MU	Change fuels and valve point	4-, 7-unit system	This approach has a straightforward idea that makes it easier to use and more successful.
[48] 2020	Cuckoo optimization	Power generation and heat limits	4 units	Enhances the exploration on the search space
[49] 2015	Coded genetic algorithm	Valve point and transmission losses	4, 5, 7, and 24 units	Effective for small and large test data
[50] 2019	MPHS		24 and 84 units	Handles large data easily
[51] 2013	MPSO	Valve point and prohibited operating zones	24 and 48 units	Toimprove the efficiency and simulation solution, Gaussian random variables were used.

5. Comparative Results and Analysis

Test case 1

The first case considered the test data of a four-unit system with one available power-only unit, two CHP units, and one available heat-only unit. The test data for this case is taken from the articles [7–9,11,13,27,32,37]. All the optimization techniques were tested for the power and heat demands of 200 MW and 115 MWth, respectively. Table 2 shows the comparative results of FA [7], MADS-DACE [8], TVAC-PSO [9], CSO [10], EMA [11], IGA-NCM [13], SFS [27], ETLBOIPSO [37], and GWO [45] for the load demand of 200 MW and heat demand of 115 MWth.

Table 2. Results obtained for the four generating units with two co-generation units and one heat unit for the load demand of 200 MW and 115 MWth.

Results of Generating Units	FA [7]	MADS–DACE [8]	TVAC-PSO [9]	CSO [10]	EMA [11]	IGA-NCM [13]	SFS [27]	ETLBOI PSO [37]	GWO [45]
P1 (MW)	0.0014	0	0	0	0	0	0	0.8473	0
P2 (MW)	159.99	160	160	160	160	160	160	159.338	160
P3 (MW)	40	40	40	40	40	40	40	39.8150	40
H2 (MWth)	40	40	40	40	40	40	40	40	40
H3 (MWth)	75	75	75	75	75	75	75	75	75
H4 (MWth)	0.0	0	0	0	0	0	0	0.18	0
Total cost ($)	9257.1	9257.07	9257.07	9257.07	9257.07	9257.07	9257.07	9178.9934	9257.07
CPU time (s)	1.25	3.27	1.78	1.18	0.9846	1.44	3.78	1.59	2.17

Figure 2 shows the total costs obtained by different optimization techniques for the load and heat demand of 200 MW and 115 MWth, respectively; out of all the techniques, it is shown that ETLBOIPSO [37] gave the best results (total cost = $9178.9934), whereas the other techniques gave almost the same results.

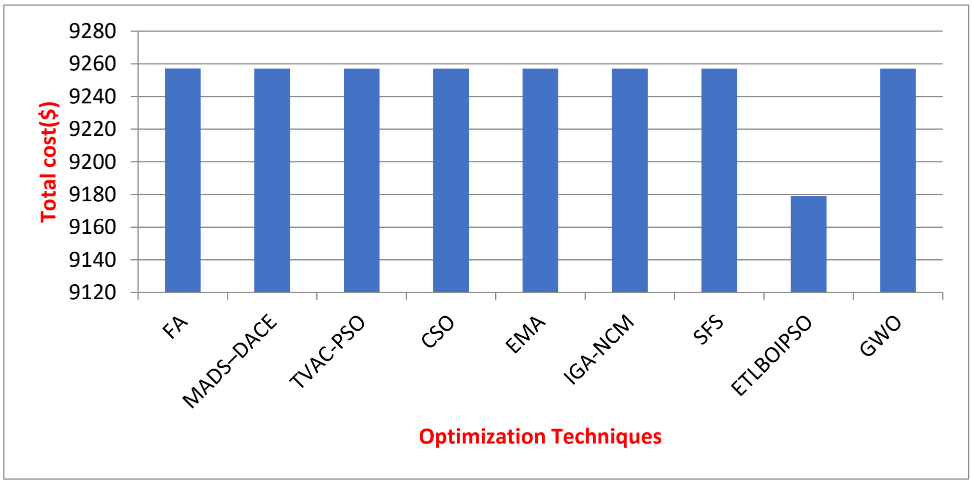

Figure 2. Total costs for load demand of 200 MW and heat demand of 115 MWth.

Test case 2

In this case study, a non-convex system with seven generating units was investigated, and the testing performances of several optimization strategies were compared. Seven units consisting of four power-only units, two CHP units, and one heat-only unit made-up this system [6,9–11,20,25,34,39]. Optimization results yielded power and heat demands of 600 MW and 150 MWth, respectively. For this case, the comparative performances of AIS [6], TVAC-PSO [9], CSO [10], EMA [11], IGA-NCM [13], HTS [34], GSO [39], GWO [45], and RCGA-I [49] are shown in Table 3. CSO [10], HTS [34], and RCGA-I [49] reported the lowest generation cost compared to other techniques, whereas EMA [11] reported the least amount of computation time. The AIS [6] techniques reported large generation costs and long computation times compared to the other algorithms.

Figure 3 shows the total costs obtained by different optimization techniques for a load demand of 600 MW and a heat demand of 150 MWth. Out of all the techniques, CSO [10] gave the best results, whereas AIS [6] gave the worst results for this case study.

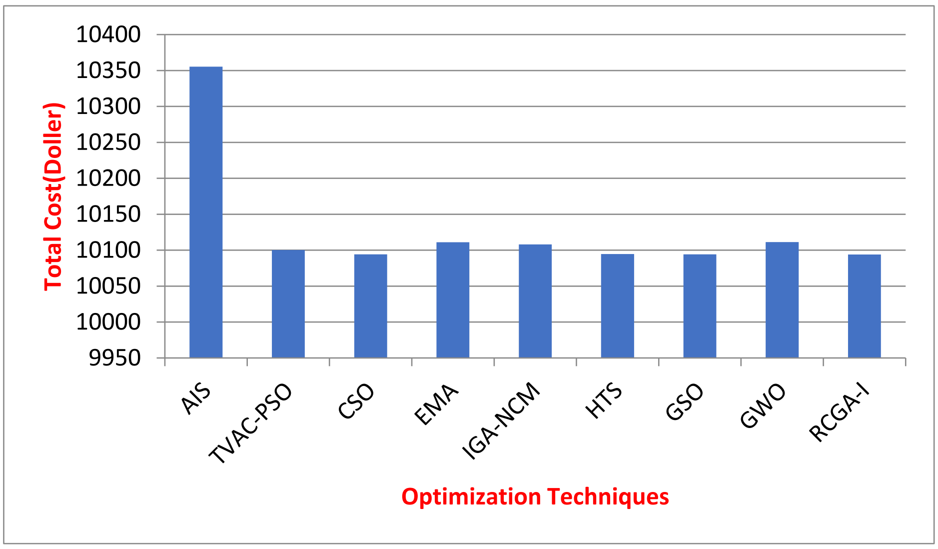

Figure 3. Total costs for load demand of 600 MW and heat demand of 150 MWth.

Table 3. Comparative performances of the various optimization techniques for the 7-unit system for the load demand of 600 MW and heat demand of 150 MWth.

Optimum Results of Generating Units	AIS [6]	TVAC-PSO [9]	CSO [10]	EMA [11]	IGA-NCM [13]	HTS [34]	GSO [39]	GWO [45]	RCGA-I [49]
P1 (MW)	50.1325	47.3383	45.2	52.684	45.155	44.2825	45.6188	52.8074	45.6614
P2 (MW)	95.5552	98.5398	98.539	98.5398	98.5398	100.110	98.5401	98.5398	98.5398
P3 (MW)	110.751	112.673	112.67	112.673	112.673	112.621	112.672	112.6735	112.6735
P4 (MW)	208.768	209.815	209.81	209.815	209.815	209.700	209.815	209.8158	209.8158
P5 (MW)	98.8	92.3718	94.183	93.8341	94.5549	94.0105	94.1027	93.8115	93.9960
P6 (MW)	42	40	40	40	40	40.0235	40.0001	40	40
H5 (MWth)	19.4242	37.8467	27.178	29.242	29.2388	28.262	27.6600	29.3704	28.2842
H6 (MWth)	77.0777	74.9999	75	75	75	74.7432	74.9987	75	75
H7 (MWth)	53.498	37.1532	47.82	45.75	45.7612	46.9948	47.3413	29.3704	46.7158
Total cost ($)	10,355	10,100.3	10,094.12	10,111.07	10,107.90	10,094.7	10,094.26	10,111.24	10,094.05
CPU time (s)	5.2956	3.48	3.09	2.06	3.47	2.01	2.4203	5.2618	3.15

Test Case 3

In this case, comparative results are shown in Table 4 for a large test data set consisting of twenty-four units (thirteen power-only units, six CHP units, and five heat-only units) [10–13,17,18,22,26,34,37]. All the algorithms were tested for power and heat demands of 2350 MW and 1250 MWth, respectively.

Table 4. Competitive results for a 24-unit system for the power and heat demands of 2350 MW and 1250 MWth.

Output	CSO [10]	EMA [11]	WOA [12]	IGA-NCM [13]	HBOA [17]	HBJSA [18]	HTS [34]	ETLBOI-PSO [37]	TLBO [44]
P1	448.7	628.31	628.3185	628.318	538.5587	448.818	539.5724	458.4	628.324
P2	225.2	299.18	299.1993	299.198	300.2175	299.2188	298.9487	291.93	298.7686
P3	299.2	299.16	299.1993	29.1665	301.08255	300.7211	297.9085	228.1	298.9086
P4	109.86	109.86	109.8665	109.867	159.777	60.10963	110.082	93.74	110.1919
P5	109.86	109.86	109.8665	109.866	63.2173	159.7451	110.2645	180	110.0846
P6	159.73	109.865	109.8665	60	60.6889	159.7769	110.2381	124.06	110.1379
P7	159.73	60	109.8665	109.86	160.20652	159.7718	110.2745	115.92	110.1045
P8	159.73	109.86	60.00003	109.823	111.5383	60	110.2452	116.68	110.2444
P9	109.86	109.856	109.8665	109.852	11.25395	159.751	110.1592	180	110.1992
P10	40	40	40.00003	40.0001	40	77.41183	77.3992	65.38	77.4989
P11	77.399	77.019	76.9485	77.0316	40.00025	40.00109	77.8364	40	77.7367
P12	92.399	55	55.00003	55.0098	55.657936	55.00862	55.0023	79.44	55.1036
P13	55	55	55.00003	55	55.284	55.6611	55.0109	89.23	55.1107
P14	87.554	81	81.00003	81.0035	87.944	85.84419	81.0524	81	81.0624
P15	40	40	40.00165	40.0003	41.2662	42.75199	40.0015	40	40.3515
P16	90.609	81	81.00003	81.0003	84.034	95.88869	81.003	81.1	81.262

Table 4. *Cont.*

Output	CSO [10]	EMA [11]	WOA [12]	IGA-NCM [13]	HBOA [17]	HBJSA [18]	HTS [34]	ETLBOI-PSO [37]	TLBO [44]
P17	40	40	40.00003	40.0001	43.1437	44.46837	40.0009	40	40.0119
P18	10	10	10.00003	10.0002	11.0824	10.04622	10.0002	10	10.0011
P19	35	35	35.00003	35.0003	35.044	35.00512	35.0001	35.012	35.0012
H14	108.47	104.82	104.8	104.801	108.697	107.4915	105.2219	104.76	105.211
H15	75	75	75.0014	75.0001	76.0921	77.37645	76.5205	75	76.5306
H16	110.19	104.82	104.8	104.799	106.47627	113.1557	105.5142	104.74	105.511
H17	75	75	75	74.9988	77.7146	78.85075	75.4833	74.99	75.4706
H18	40	40	40	39.9993	40.4643	40.02	39.9999	40	39.9999
H19	20	20	20	20.0001	20.0204	20.00127	18.3944	18.25	18.4014
H20	461.32	470.39	470.3986	470.409	460.53781	453.1093	468.9043	473	468.902
H21	59.999	60	59.99998	60	60	60	59.9994	60	59.9995
H22	59.999	60	59.99998	60	60	59.99883	59.9999	59.96	59.9995
H23	119.99	120	119.9999	120	119.99644	119.9964	119.9854	119.35	119.9856
H24	120	120	119.9999	119.991	120	119.9995	119.9768	119.99	119.986
Total cost ($)	57,907.1	57,825.5	57,830.52	57,826.09	57,994.51	57,968.54	57,842.99	57,758.66	57,843.52
CPU (s)	24.98	1.167	2.71	1.72	3.62	4.04	5.47	2.63	5.4106

Table 4 shows the comparative results of the CSO [10], EMA [11], WOA [12], IGA-NCM [13], HBOA [17], HBJSA [18], HTS [34], ETLBOI-PSO [37], and TLBO [44] techniques for a 24-unit problem system. All the algorithms performed well, but the ETLBOI-PSO [37] technique gave a minimum generation cost of 57,758.66 dollars, which is the best out of all the other methods. EMA [11] reported the least computation time.

Figure 4 shows the total costs obtained by different optimization techniques for a load and heat demand of 2350 MW and 1250 MWth, respectively. In this case, ETLBOI-PSO [37] gave the best results, whereas HBOA [17] gave the worst results.

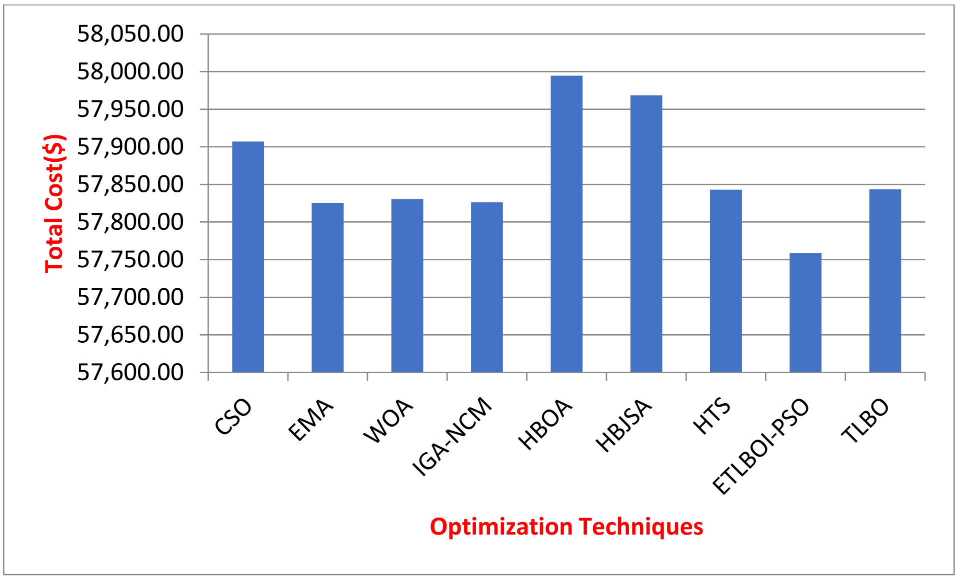

Figure 4. Total costs for power and heat demands of 2350 MW and 1250 MWth, respectively.

Test Case 4

This case study took data from a large system with non-convex fuel costs [10,11,18,29–31,36,37]. These large test system had 48 units (26 power-only units, twelve CHP units, and ten heat-only units). The comparative results of the new heuristic optimization techniques for the power and heat demands of 4700 MW and 2500 MWth, respectively, are shown in Table 5. Compared to all the other techniques, KKO [28] gavea minimum cost of $115,422, whereas the OQNLP [29] technique reported a generation cost of $116,993.2, which was the maximum, compared to the other methods.

Table 5. Costs obtained by different heuristic optimization techniques for the 48-unit system (power and heat demands of 4700 MW and 2500 MWth).

Methods	Min. Cost ($)	Methods	Min. Cost ($)
CSO [10]	115,967.7205	OQNLP [29]	116,993.2
EMA [11]	115,611.84	IMPAO [30]	116,640.6
IGA_NCM [13]	115,685.2	CLWSMA [31]	116,389.588
HBJSA [18]	116,140.34	TVAC-PSO [36]	115,610.465
OGSO [19]	116,678.2	ETLBOIPSO [37]	115,126.32
MGSO [24]	115,606.5482	COA [42]	116,789.91535
TVAC-GSA-PSO [25]	116,393.4034	TLBO [44]	116,739.3640
KKO [28]	115,422	OTLBO [44]	116,579.2390
		MPSO [51]	116,919

Figure 5 shows the total costs obtained by different optimization techniques for a load and heat demand of 4700 MW and 2500 MWth, respectively. In this case, ETLBOI-PSO [37] gave the best results, whereas OQNLP [29] gave the worst results.

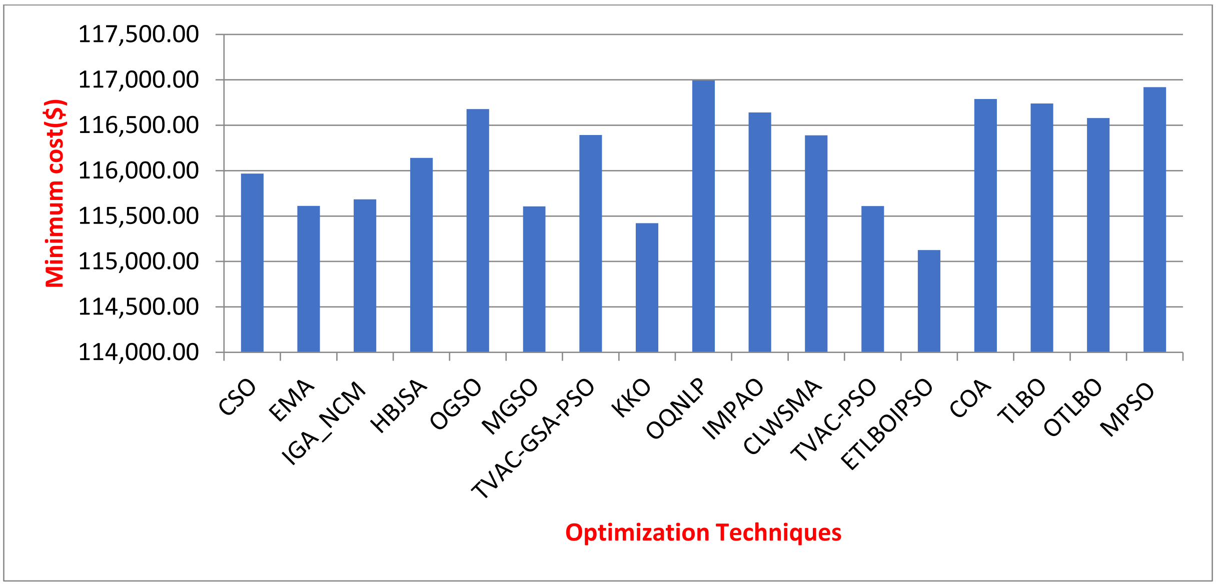

Figure 5. Total costs for power and heat demands of 4700 MW and 2500 MWth, respectively.

Test Case 5

In this case, a large test system of 84 units was taken into consideration. This test case had 40 generating, 24 cogeneration, and 20 heat-only units [12,30,31]. The test results of various optimization techniques for the 84-unit system (5000 MWth and 12,700 MW of heat and power demands, respectively) are shown in Table 6. The MPHS [50] techniques reported a minimum generation cost of $288,157.4297, which was a minimum compared to all the other techniques, and it took 76.65 s to compute, which was also the least amount of computation time, compared to all the other listed techniques in Table 6.

Table 6. Test results for the test data of 84-unit system.

Methods	Minimum Cost ($)	CPU Time (s)
TVAC-PSO [9]	295,680.9138	90.21
WOA [12]	290,123.97424	158.18
HBOA [17]	289,822.39	114.5
IMPAO [30]	289,903.8	134.4
CLWSMA [31]	288,698.9636	124.2
SMA [31]	288,978.8	89.5
CODED GENETIC ALGORITHM [49]	298,417.18704	140.91
MPHS [50]	288,157.4297	76.65

Figure 6 shows the total costs obtained by the different optimization techniques for a load and heat demand of 12,700 MW and 5000 MWth, respectively. In this case, CLWSMA [31] gave the best results, whereas CODED GENETIC ALGORITHM [49] gave the worst results.

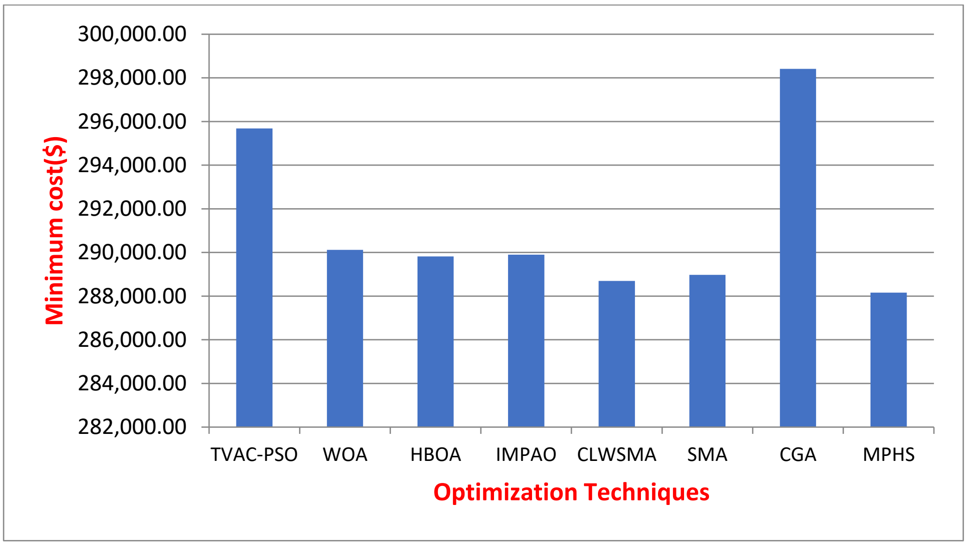

Figure 6. Total costs for power and heat demands of 12,700 MW and 5000 MWth, respectively.

Test Case 6

In this case, again, a larger test data set of a 96-unit system was available, with 52 traditional power units, 24 cogeneration units, and 20 heat-only units [12,17,30,31]. All the algorithms' comparative results are listed in Table 7 for the load demand of 9400 MW and the heat demand of 5000 MWth. The CLWSMA [31] method reported a minimum generation cost of $235,083.367, which was the least, compared to the other listed techniques in Table 7.

Table 7. Cost of 96-unit system for the load demand of 9400 MW and heat demand of 5000 MWth.

Methods	Min. Cost ($)
TVAC-PSO [9]	239,139.50
WOA [12]	236,699.1501
HBOA [17]	235,102.65
IMPAO [30]	235,260.3
CLWSMA [31]	235,083.367
SMA [31]	235,973.3
RCGA-IMM [49]	239,896.41

Figure 7 shows the total costs obtained by different optimization techniques for a load and heat demand of 9400 MW and 5000 MWth, respectively. In this case, HBOA [17] gave the best results, whereas RCGA-IMM [49] gave the worst results.

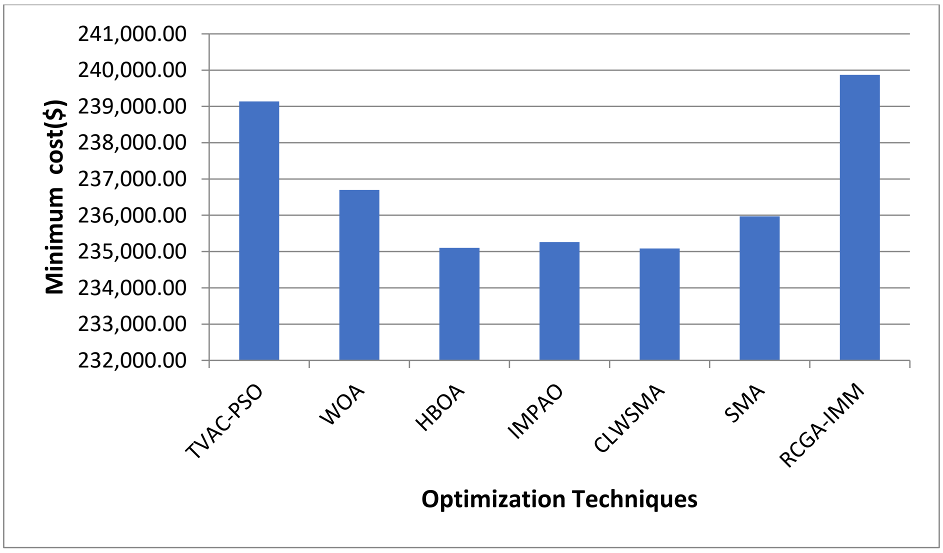

Figure 7. Total costs for load and heat demands of 9400 MW and 5000 MWth.

6. Conclusions

This article presents a deep analysis of various heuristic optimization techniques used for the optimum solution of CHPED. The CHPED problem is formulated along with various constraints shown in Table 1, which increase the complexity of the system and make classical optimization methods ineffective at finding an optimal solution. Numerous population-based heuristic optimization approaches have now been used to solve the CHPED issue in order to address the deficiencies of traditional optimization techniques. In this article, we consider many of the heuristic optimization techniques shown in Table 1, which are used to solve the CHPED problems with different load and heat demand conditions. Some methods are used to solve small generating units, such as 4, 7, and 24 units, while others are used for large generating units, such as 48-, 84-, and 96-unit systems. In this article, we try to show the effectiveness of optimization techniques for small generating units in a large available unit system. This study covered six cases for different unit systems. It is observed that almost all techniques are able to solve the CHPED problem in a very short amount of computation time. As in case 1, almost all the methods give the same results; only the computation time is different. The WOA [12], the heap-based optimization algorithm (HBOA) [17], the hybrid heap-based and jellyfish search algorithms [18], the modified group search optimizer [24], the comprehensive learning wavelet-mutated slime mold algorithm [31], the differential evolution [35], and the MPHS [50] techniques are found effective for small as well as large generating unit systems. For all the methods, the results are similar to each other, but in some cases, the results from two to three techniques are better in terms of minimum generation cost, which is already explained in the results analysis section.

Author Contributions: Conceptualization, N.S. and P.C.; methodology, N.S., T.C., D.B. and V.B.; software, N.S. and T.C.; validation, V.P., D.B. and V.B.; formal analysis, T.C., P.C. and V.B.; investigation, N.S. and T.C.; resources, P.C.; data curation, V.P., D.B., I.Y. and V.B.; writing—original draft preparation, N.S., T.C. and D.B.; writing—review and editing, V.P. and V.B.; visualization, N.S., V.P., and I.Y.; supervision, P.C. and V.B.; project administration, P.C.; funding acquisition, P.C.,V.P., D.B., I.Y. and V.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

AI	Artificial immune
BCO	Bee colony optimization
BLPSO	Biogeography-based learning particle swarm optimization
CHPED	Combined heat-power economic dispatch
C_i	Total generation cost
C_j	Generation cost with CHP units
C_k	Generation cost using heat-only units
CSA-BA-ABC	Artificial bee colony
C-PSO	Co-evolutionary particle swarm optimization
CSO	Civilized swarm optimization
COA	Cuckoo optimization algorithm
Np	Number of power-only units
Nc	CHP units
Ck	Heat-only units
ECSA	Elitist cuckoo search algorithm
GWO	Grey wolf optimization
GSO	Group search optimization
GAMS	General algebraic modeling system
HBOA	Heap-based optimization algorithm
HTSA	Heat transfer search algorithm
HBJSA	Hybrid heap-based and jellyfish search algorithm
IGA-NCM	Improved genetic algorithm
IDE	Improved differential evolution
IMPA	improved marine predators algorithm
MPSO	Modified particle swarm optimization
MGSO	Modified group search optimizer
OQNLP	OptQuest/NLP
PPS	Powell's pattern search
SPSO	Selective particle swarm optimization
TVAC-PSO	Time varying acceleration coefficient particle swarm optimization
WOA	Whale optimization algorithm
SFS	Stochastic fractal search algorithm

References

1. Rooijers, F.J.; van Amerongen, R.A. Static economic dispatch for co-generation systems. *IEEE Trans. Power Syst.* **1994**, *9*, 1392–1398. [CrossRef]
2. Guo, T.; Henwood, M.I.; van Ooijen, M. An algorithm for combined heat and power economic dispatch. *IEEE Trans. Power Syst.* **1996**, *11*, 1778–1784. [CrossRef]
3. Abdolmohammadi, H.R. A benders decomposition approach for a combined heat and power economic dispatch. *Energy Conserv. Manag.* **2013**, *71*, 21–31. [CrossRef]
4. Ramesh, V.; Jayabarathi, T.; Shrivastava, N.; Baska, A. A novel selective particle swarm optimization approach for combined heat and power economic dispatch. *Electr. Power Compon. Syst.* **2009**, *37*, 1231–1240. [CrossRef]
5. Basu, M. Bee colony optimization for combined heat and power economic dispatch. *Expert Syst. Appl.* **2011**, *38*, 13527–13531. [CrossRef]
6. Basu, M. Artificial immune system for combined heat and power economic dispatch. *Int. J. Electr. Power Energy Syst.* **2012**, *43*, 1–5. [CrossRef]
7. Yazdani, A.; Jayabarathi, T.; Ramesh, V.; Raghunathan, T. Combined heat and power economic dispatch problem using firefly algorithm. *Front. Energy* **2013**, *7*, 133–139. [CrossRef]
8. Hosseini, S.S.S.; Jafarnejad, A.; Behrooz, A.H.; Gandomi, A.H. Combined heat and power economic dispatch by mesh adaptive direct search algorithm. *Expert Syst. Appl.* **2011**, *38*, 6556–6564. [CrossRef]
9. Mohammadi-Ivatloo, B.; Moradi-Dalvand, M.; Rabiee, A. Combined heat and power economic dispatch problem solution using particle swarm optimization with time varying acceleration coefficients. *Electr. Power Syst. Res.* **2013**, *95*, 9–18. [CrossRef]
10. Meng, A.; Mei, P.; Yin, H.; Peng, X.; Guo, Z. Crisscross optimization algorithm for solving combined heat and power economic dispatch problem. *Energy Convers. Manag.* **2015**, *105*, 1303–1317. [CrossRef]
11. Ghorbani, N. Combined heat and power economic dispatch using exchange market algorithm. *Electr. Power Energy Syst.* **2016**, *82*, 58–66. [CrossRef]
12. Nazari-Heris, M.; Mehdinejad, M.; Mohammadi-Ivatloo, B.; Babamalek-Gharehpetian, G. Combined heat and power economic dispatch problem solution by implementation of whale optimization method. *Neural Comput. Appl.* **2017**, *31*, 421–436. [CrossRef]
13. Zou, D.; Li, S.; Kong, X.; Ouyang, H.; Li, Z. Solving the combined heat and power economic dispatch problems by an improved genetic algorithm and a new constraint handling strategy. *Appl. Energy* **2019**, *237*, 646–670. [CrossRef]
14. Neyestani, M.; Hatami, M.; Hesari, S. Combined heat and power economic dispatch problem using advanced modified particle swarm optimization. *J. Renew. Sustain. Energy* **2019**, *11*, 015302. [CrossRef]
15. Sundaram, A. Combined Heat and Power Economic Emission Dispatch Using Hybrid NSGA II-MOPSO Algorithm Incorporating an Effective Constraint Handling Mechanism. *IEEE Access* **2020**, *8*, 13748–13768. [CrossRef]
16. Singh, N. A New PSO Technique Used for the Optimization of Multiobjective Economic Emission Dispatch. *Electronics* **2023**, *12*, 2960. [CrossRef]
17. Ginidi, A.R.; Elsayed, A.M.; Shaheen, A.M.; Elattar, E.E.; El-Sehiemy, R.A. A Novel Heap-Based Optimizer for Scheduling of Large-Scale Combined Heat and Power Economic Dispatch. *IEEE Access* **2021**, *9*, 83695–83708. [CrossRef]
18. Ginidi, A.; Elsayed, A.; Shaheen, A.; Elattar, E.; El-Sehiemy, R. An Innovative Hybrid Heap-Based and Jellyfish Search Algorithm for Combined Heat and Power Economic Dispatch in Electrical Grids. *Mathematics* **2021**, *9*, 2053. [CrossRef]
19. Basu, M. Combined heat and power economic dispatch using opposition-based group search optimization. *Electr. Power Energy Syst.* **2015**, *73*, 819–829. [CrossRef]
20. Beigvand, S.D.; Abdi, H.; La Scala, M. Combined heat and power economic dispatch problem using gravitational search algorithm. *Electr. Power Syst. Res.* **2016**, *133*, 160–172. [CrossRef]
21. Chen, X.; Li, K.; Xu, B.; Yang, Z. Biogeography-based learning particle swarm optimization for combined heat and power economic dispatch problem. *Knowl.-Based Syst.* **2020**, *208*, 106463. [CrossRef]
22. Nguyen, T.T.; Vo, D.N.; Dinh, B.H. Cuckoo search algorithm for combined heat and power economic dispatch. *Electr. Power Energy Syst.* **2016**, *81*, 204–214. [CrossRef]
23. Narang, N.; Sharma, E.; Dhillon, J.S. Combined heat and power economic dispatch using integrated civilized swarm optimization and Powell's pattern search method. *Appl. Soft Comput.* **2017**, *52*, 190–202. [CrossRef]
24. Davoodi, E.; Zare, K.; Babaei, E. A GSO-based algorithm for combined heat and power dispatch problem with modified scrounger and ranger operators. *Appl. Therm. Eng.* **2017**, *120*, 36–48. [CrossRef]
25. Beigvand, S.D.; Abdi, H.; La Scala, M. Hybrid Gravitational Search Algorithm-Particle Swarm Optimization with Time Varying Acceleration Coefficients for Large Scale CHPED Problem. *Energy* **2017**, *126*, 841–853. [CrossRef]
26. Murugan, R.; Mohan, M.R.; Rajan, C.C.A.; Sundari, P.D.; Arunachalam, S. Hybridizing Bat Algorithm with Artificial Bee Colony for Combined Heat and Power Economic Dispatch. *Appl. Soft Comput.* **2018**, *72*, 189–217. [CrossRef]
27. Alomoush, M.I. Optimal Combined Heat and Power Economic Dispatch Using Stochastic Fractal Search Algorithm. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 276–287. [CrossRef]
28. Srivastava, A.; Das, D.K. A new Kho-Kho optimization Algorithm: An application to solve combined emission economic dispatch and combined heat and power economic dispatch problem. *Eng. Appl. Artif. Intell.* **2020**, *94*, 103763. [CrossRef]
29. Nazari-Heris, M.; Mohammadi-Ivatloo, B.; Zare, K.; Siano, P. Optimal generation scheduling of large-scale multi-zone combined heat and power systems. *Energy* **2020**, *210*, 118497. [CrossRef]

30. Shaheen, A.M.; Elsayed, A.M.; Ginidi, A.R. A novel improved marine predators algorithm for combined heat and power economic dispatch problem. *Alex. Eng. J.* **2022**, *61*, 1834–1851. [CrossRef]
31. Pawani, K.; Singh, M. Combined Heat and Power Dispatch Problem Using Comprehensive Learning Wavelet-Mutated Slime Mould Algorithm. *Electr. Power Compon. Syst.* **2023**, *51*, 12–28. [CrossRef]
32. Ohaegbuchi, D.N.; Maliki, O.S.; Okwaraoka, C.P.A.; Okwudiri, H.E. Solution of Combined Heat and Power Economic Dispatch Problem Using Direct Optimization Algorithm. *Energy Power Eng.* **2022**, *14*, 737–746. [CrossRef]
33. Hosseini, S.E.; Najafi, M.; Akhavein, A. Day-Ahead Scheduling for Economic Dispatch of Combined Heat and Power loss with Uncertain Demand Response. *IEEE Access* **2022**, *10*, 42441–42458. [CrossRef]
34. Pattanaik, J.K.; Basu, M.; Dash, D.P. Heat Transfer Search Algorithm for Combined Heat and Power Economic Dispatch. Iranian Journal of Science and Technology. *Trans. Electr. Eng.* **2020**, *44*, 963–978.
35. Zou, D.; Gong, D. Differential evolution based on migrating variables for the combined heat and power dynamic economic dispatch. *Energy* **2022**, *238*, 121664. [CrossRef]
36. Nourianfar, H.; Abdi, H. Solving the multi-objective economic emission dispatch problems using Fast Non-Dominated Sorting TVAC-PSO combined with EMA. *Appl. Soft Comput.* **2019**, *85*, 105770. [CrossRef]
37. Goudarzi, A.; Ni, S.F.J.; Ghayoor, F.; Siano, P.; Alhelou, H.H. Sequential hybridization of ETLBO and IPSO for solving reserve-constrained combined heat, power and economic dispatch problem. *IET Gener. Transm. Distrib.* **2022**, *16*, 1930–1949. [CrossRef]
38. Sundaram, A. Multiobjective multi-verse optimization algorithm to solve combined economic, heat and power emission dispatch problems. *Appl. Soft Comput.* **2020**, *91*, 106195. [CrossRef]
39. Basu, M. Group search optimization for combined heat and power economic dispatch. *Electr. Power Energy Syst.* **2016**, *78*, 138–147. [CrossRef]
40. Geem, Z.W.; Cho, Y.-H. Handling non-convex heat-power feasible region in combined heat and power economic dispatch. *Int. J. Electr. Power Energy Syst.* **2012**, *34*, 171–173. [CrossRef]
41. Bahmani-Firouzi, B.; Farjah, E.; Seifi, A. A new algorithm for combined heat and power dynamic economic dispatch considering valve-point effects. *Energy* **2013**, *52*, 320–332. [CrossRef]
42. Mehdinejad, M.; Mohammadi-Ivatloo, B.; Dadashzadeh-Bonab, R. Energy production cost minimization in a combined heat and power generation systems using cuckoo optimization algorithm. *Energy Effic.* **2017**, *10*, 81–96. [CrossRef]
43. Beigvand, S.D.; Abdi, H.; La Scala, M. An improved differential evolution algorithm for the economic load dispatch problems with or without valve-point effects. *Electr. Power Syst. Res.* **2016**, *181*, 375–390.
44. Roy, P.K.; Paul, C.; Sultana, S. Oppositional teaching learning based optimization approach for combined heat and power dispatch. *Electr. Power Energy Syst.* **2014**, *57*, 392–403. [CrossRef]
45. Jayakumar, N.; Subramanian, S.; Ganesan, S.; Elanchezhian, E.B. Grey wolf optimization for combined heat and power dispatch with cogeneration systems. *Electr. Power Energy Syst.* **2016**, *74*, 252–264. [CrossRef]
46. Shi, B.; Yan, L.-X.; Wu, W. Multi-objective optimization for combined heat and power economic dispatch with power transmission loss and emission reduction. *Energy* **2013**, *56*, 135–143. [CrossRef]
47. Chiang, C.-L. Improved Genetic Algorithm for Power Economic Dispatch of Units with Valve-Point Effects and Multiple Fuels. *IEEE Trans. Power Syst.* **2005**, *20*, 1690–1702. [CrossRef]
48. Mellal, M.A.; Williams, E.J. Cuckoo optimization algorithm with penalty function for combined heat and power economic dispatch problem. *Energy* **2015**, *93*, 1711–1718. [CrossRef]
49. Haghrah, A.; Nazari-Heris, M.; Mohammadi, B. Solving combined heat and power economic dispatch problem using real coded genetic algorithm with improved Mühlenbein mutation. *Appl. Therm. Eng.* **2016**, *99*, 465–475. [CrossRef]
50. Nazari-Heris, M.; Mohammadi-Ivatloo, B.; Asadi, S.; Geem, Z.W. Large-scale combined heat and power economic dispatch using a novel multi-player harmony search method. *Appl. Therm. Eng.* **2019**, *154*, 493–504. [CrossRef]
51. Basu, M. Modified Particle Swarm Optimization for Non-smooth Non-convex Combined Heat and Power Economic Dispatch. *Electr. Power Compon. Syst.* **2015**, *43*, 2146–2155. [CrossRef]
52. Yang, Q.; Gao, H.; Dong, N.; Liu, P. An elitist cuckoo search algorithm for combined heat and power economic dispatch. *Int. J. Prod. Res.* **2023**, *43*, 1–16. [CrossRef]
53. Singh, N. Novel Heuristic Optimization Technique to Solve Economic Load Dispatch and Economic Emission Load Dispatch Problems. *Electronics* **2023**, *12*, 2921. [CrossRef]