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Review

Optimization of Combined Heat and Power Systems by Meta-Heuristic Algorithms: An Overview

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Abstract: Combined heat and power (CHP) plants are known as efficient technologies to reduce environmental emissions, balance energy costs, and increase total energy efficiency. To obtain a more efficient system, various optimization methods have been employed, based on numerical, experimental, parametric, and algorithmic optimization routes. Due to the significance of algorithmic optimization, as a systematic method for optimizing energy systems, this novel review paper is focused on the meta-heuristic optimization algorithms, implemented in CHP energy systems. By considering the applied objective functions, the main sections are divided into single-objective and multi-objective algorithms. In each case, the units' combination is briefly detailed, the objective functions are introduced, and analyses are conducted. The main aim of this paper is to gather a database for the optimization of CHPs, demonstrate the effect of the applied optimization methods on the objective functions, and finally, introduce the most efficient methods. The most significant feature of this paper is that it covers all types of CHP optimization issues including scheduling, sizing, and designing problems, finding the extent of each optimization issue in the relevant papers in the last decade. Based on the findings, in the single-objective problems the combined heat and power economic dispatch (CHPED) issue as a subcategory of the scheduling problems is introduced as the most paid topic; the designing issue is known as the lowest paid topic. In the multi-objective problems, working on various types of CHP optimization problems has been conducted with an almost similar share. The combined heat and power economic emission dispatch (CHPEED) problem with the most share, and the sizing issue with the lowest share. The CHP designing and sizing optimization issues could be introduced as topics to work on more in the future. Additionally, the numerical results of CHPED and CHPEED problems solved by various algorithms are presented and compared. In this regard, specified test systems are considered.

Keywords: combined heat and power; energy optimization; meta-heuristic; evolutionary algorithms

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1. Introduction

The lack of fossil fuel resources and many problems caused by these energy resources consumption, such as negative environmental impacts and climate change on one side, and growing energy demands, on the other side, have forced the researchers and engineers in the relevant fields to provide better alternatives [1]. As a basic solution, the presentation of efficient energy production systems can have a tremendous impact on reducing energy consumption, and environmental issues. Combined heat and power (CHP) energy systems, as highly efficient systems, generate two forms of useful energy: electricity and heat [2]. In comparison to a traditional power plant, with about 35% electricity generation efficiency, the overall efficiency of the CHP plant could be over 80%. Since most CHP applications are for on-site generation, known as distributed generation (DG), these types of technologies cause the reduction of energy loss and increase efficiency. On the other hand, the recovery of the waste heat causes a significant rise in the system efficiency [3]. Generally, CHP plants have plenty of advantages in terms of reducing primary energy consumption and improving the economic and environmental specifications of a plant [4].

Since an optimization process is vital for designing any energy system, various studies have focused on this subject. The optimization of CHP plants has been carried out in many papers, in different ways. Silveira et al. [5,6] optimized some CHP plants mathematically, through a thermoeconomic model. In another paper, an efficient stochastic integer linear programming method was used for the optimal allocating of a CHP plant [7]. An optimal operation of CHP plants, maximizing the revenue, and minimizing the operating cost, was obtained through an optimization-based controller using the economic model predictive control (EMPC) approach [8]. A mathematical optimization model of a biomass-based CHP plant was presented by Asni et al. [9]. They applied a multi-objective fuzzy strategy in the presented model. Other mathematical optimization models have also been applied to the CHP optimization issues [10–12]. The mathematical methods obtain exact solutions of an optimization problem, but this approach is not practical for some engineering issues. This is mainly because of the difficulty of harvesting the derivative information analytically. The meta-heuristic algorithms are appropriate alternatives for CHP optimization. The process of these methods is the generation of arbitrary initial approximations to the problem, and the improvement of the generated solutions [13]. In this paper, the application of the meta-heuristic methods, for the CHP optimization problems, has been studied. The population-based meta-heuristics, as a large category of these methods, have been reviewed and divided. The classification is shown in Figure 1.

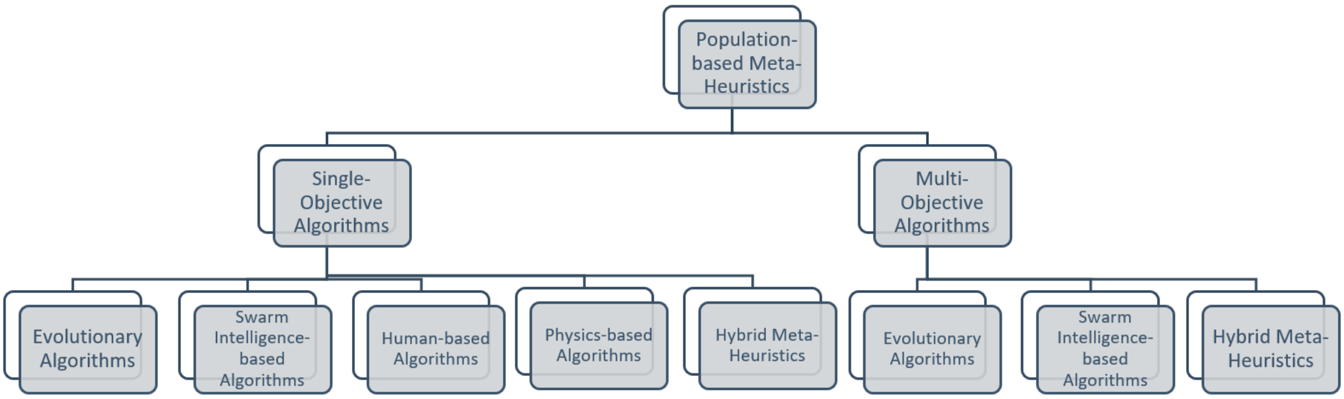

Figure 1. Classification of the population-based Meta-Heuristic algorithms.

Few review papers address the CHP optimization issues. In this area, Abusoglu et al. [14], reviewed various exergoeconomic optimization models of CHP plants. In another review study, by Nazari-Heris et al. [15], the application of various meta-heuristic methods, as the solvers of a determined CHP optimization problem, was presented. The studied problem was on the CHP economic dispatch systems. Kazda et al. [16] reviewed the presented models of economic dispatch, and economic and emission dispatch of CHP plants. In the above-mentioned review papers, mostly the optimal dispatching issues were considered as the optimization problems. Additionally, exergoeconomic, economic, and emission issues were considered as the problem objectives; the application of meta-heuristic methods for CHP optimization was reviewed limitedly. However, in this paper, besides the dispatching optimization problems, all types of CHP optimization issues, including the optimal designing, sizing, and scheduling are reviewed, and various objective functions are covered, such as energy consumption, electrical efficiency, social welfare, primary energy saving, etc. For investigating the performance of different optimization methods, first, based on the reviewed papers, the CHP economic dispatch (CHPED) and the CHP economic emission dispatch (CHPEED) problems are selected as the most considered single-objective and multi-objective optimization issues, respectively. Then, the numerical results of various meta-heuristic algorithms applied to solve these problems are compared. Additionally, a comprehensive presentation of various optimization models of CHP plants, in the two forms of single-objective and multi-objective, is presented at the end of each chapter. In this paper, the population-based meta-heuristics in single-objective optimization are studied in five sections including evolutionary algorithms (EAs), swarm intelligence-based algorithms (SI-based), human-based algorithms, physics-based algorithms, and hybrid meta-heuristic methods. Additionally, for multi-objective optimization, three sections, including the EAs, SI-based algorithms, and hybrid meta-heuristic methods are presented.

2. Single-Objective Algorithms for CHP Optimization

The issues, which optimize one objective function, are called the single-objective optimization problems. The process of the algorithms used to solve these issues ends to maximize or minimize a specific purpose.

2.1. Evolutionary Algorithms

Evolutionary algorithms, which are inspired by evolution in nature, are one of the subcategories of population-based meta-heuristic algorithms. In evolutionary algorithms, the search process to find the best solution starts with a randomly-generated population and continues through evolving the population during consecutive generations [17].

- Genetic Algorithms

The genetic algorithms (GAs) were developed by Holland [18] based on the growth and decay of living organisms in a natural environment and could be introduced as the most practical evolutionary algorithms. The GAs have been used in various kinds of optimization problems and proved themselves as effective methods. For example, the CHP design optimization problem leads to selecting the optimal design among many alternatives according to design variables, such as isentropic efficiency, temperature, pressure ratio, etc. In 2010, Ahmadi et al. [19] applied the GA to optimize a typical CHP plant by minimizing the plant's total cost, considering the cost of environmental impacts and the cost of exergy destruction. The optimization caused a 9.80% improvement in the total cost. They considered compressor isentropic efficiency, compressor pressure ratio, gas turbine isentropic efficiency, turbine inlet temperature, and combustion chamber inlet temperature as the design parameters. In another study by Mohammadkhani et al. [20], an optimization process was carried out via the GA for a diesel engine-based CHP system. The objective function considered the total cost of the system product and the cost of exergy destruction and was decreased by 8.02%. These studies showed the importance of the exergoeconomic analysis in gaining a cost-optimal design. In another designing optimization problem, Arsalis et al. [21] presented an optimal design of a fuel cell-based micro-CHP, while the net electrical efficiency of the system was maximized using the genetic algorithm. In another optimal designing issue, in 2021, Dimri et al. [22] used the GA to achieve the optimal design of different solar CHP plants. This optimization was based on a thermoeconomic indicator.

Optimal sizing, as another optimization problem in the CHP plants, is vital in terms of saving energy sources and reducing energy costs. In a study, a quick method for sizing and determining the amount of equipment in a combined heat and power natural gas pressure reduction plant was presented; the GA was applied for maximizing the actual annual benefit [23]. The robust ability of the fit-problem GA was proved by Ferreira et al. [24] by carrying out a comparison among the performance of the GA, the sequential quadratic programming (SQP), and the pattern search (PS) method in the optimal sizing of a CHP plant. The fit-problem GA applied the population size and mutation probability updating strategies and led to better solutions and a faster convergence rate. In another study, Yu et al. [25] obtained the optimal capacity of a CHP plant by minimizing the daily energy costs. They used the maximum rectangle (MR) method and the genetic algorithm. The GA obtained a lower average energy cost, while higher energy efficiency was obtained by the MR method. In that case, the MR method was preferred to the GA, because of its full use of the CHP capacity and its shorter computation time.

The combined heat and power economic dispatch (CHPED) issue, as a complicated highly-constrained optimization problem, has been noticed by researchers in various studies. This problem achieves the optimum values of the heat and power production, which causes the minimum point of the system total fuel cost, considering the power and heat load demands and other constraints. An algorithm called the real coded genetic algorithm with improved Mühlenbein mutation (RCGA-IMM) was presented by Haghrah et al. [26] for accelerating and improving the convergence characteristics of the real coded GA in solving the CHPED problem. They considered the effect of valve point and transmission loss on the production cost and power production terms. In another CHPED optimization problem, in 2019, an improved genetic algorithm, using novel crossover and mutation (IGA-NCM), was presented by Zou et al. [27]. The selection process was excluded from the GA, to preserve the population diversity as well. Additionally, in another study by Haghrah et al. [28], a novel real-coded genetic algorithm with the random walk-based mutation was applied to solve the CHPED problem. They concluded this novel algorithm could achieve accurate results.

The CHP energy systems could perform in a hybrid way by applying various energy resources or components alongside the other generation units in a microgrid (MG). In both cases, the proper dispatching among the resources loads, or different units, which are called scheduling optimization problems, leads to an optimal energy system. Optimal scheduling of a solar fossil-fueled CHP plant, combined with a thermal storage and dispatch system, was carried out by Abdelhady et al. [29]. The schematic of the hybrid CHP is shown in Figure 2. After minimizing the external utilities, the GA algorithm was employed to obtain the optimal generated power and distribution of thermal energy among fossil, solar direct, and solar stored/dispatched resources. The results for January, as a typical month, are shown in Figure 3. In another scheduling problem, Shang et al. [30] optimized a storage-integrated generation model of a CHP plant, to minimize fuel consumption, via the non-dominated sorting genetic algorithm II (NSGA- II). Maleki et al. [31] presented the optimal scheduling of a grid-connected solar-wind-hydrogen CHP system to minimize the total cost of the plant by the GA and particle swarm optimization algorithm (PSO). They found that the GA can achieve better results rather than the PSO.

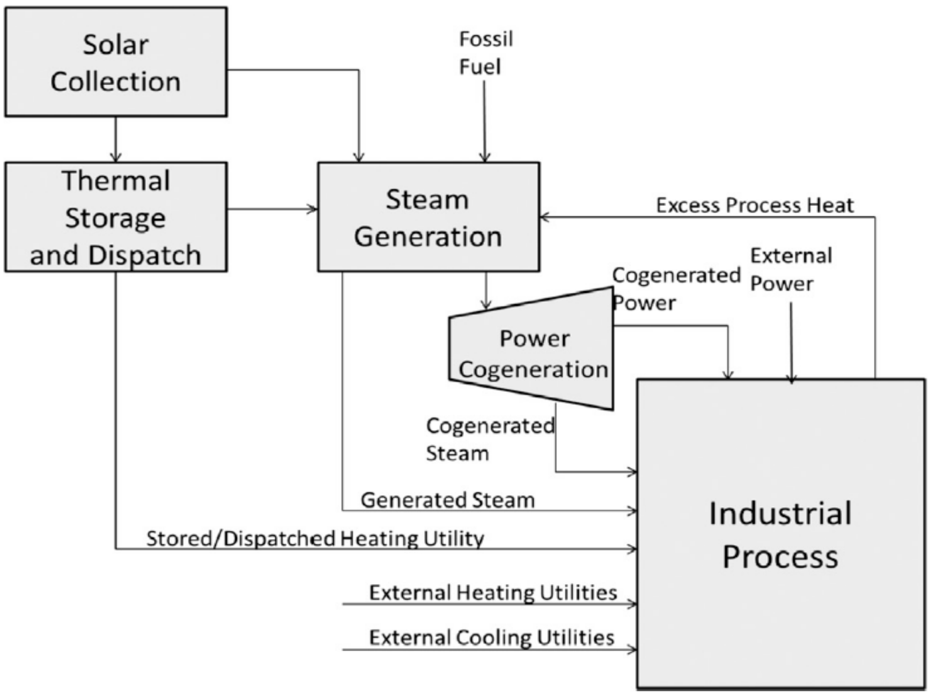

Figure 2. Schematic of the solar fossil-fueled CHP plant combined with a thermal storage and dispatch system [29].

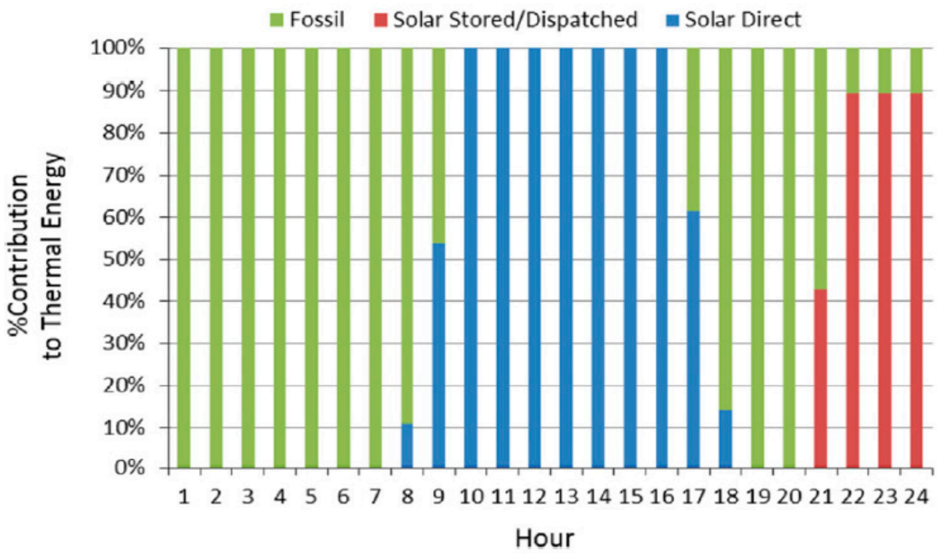

Figure 3. Hourly contribution of the thermal energy resources during January [29].

- Differential Evolution Algorithms

The differential evolution (DE) algorithm, as a type of evolutionary algorithm, is an improved combination of the genetic algorithm with the evolutionary programming (EP), that was first introduced in 1997 [32]. In 2010, Basu [33] applied the DE algorithm to solve the CHPED problem. It was applied in a test system, composed of four conventional power generation plants, two CHP systems, and a heat generation unit. For comparison, the particle swarm optimization (PSO) and EP algorithms were implemented in the test system. The comparison showed that the DE obtained a lower cost and computation time than the PSO and EP algorithms. Basu [34], in another study, used the DE algorithm to obtain optimal planning of the fuel energy consumption of various distributed energy resources (DER) in a CHP-based microgrid. The planning was performed through two stages, including optimal sizing and economic scheduling. To improve the performance of the DE algorithm, various strategies were applied by some researchers. For example, the self-adaptive DE algorithm (SADE) was presented by Venkatakrishnan et al. [35], to overcome the long time needed for fine-tuning the parameters in solving the economic dispatch problems of a grid-connected fuel cell-based CHP. In another study, by Jena et al. [36], the Gaussian mutation operator was applied in the DE algorithm (DEGM) to improve the search ability of the DE in solving the CHPED problem. the total cost of the plant, which was obtained at 9235.1032 $ showed the great ability of this algorithm, compared to the other methods. An improved version of the DE (IDE), which used a double variation differential strategy, was applied by Wang et al. [37] in solving a scheduling optimization problem for an integrated energy system. Additionally, Zou et al. [38] used the DE algorithm based on migrating variables to solve the CHP dynamic economic dispatch. In a CHPED problem, the self-adaptive DE algorithm combined with Gaussian–Cauchy mutation was applied by Chen et al. [39].

- Other Evolutionary Algorithms

In addition to the aforementioned algorithms, there are some other evolutionary methods, which were applied in the CHP optimization cases. The artificial immune system (AIS), the hyper-spherical search (HSS), and the stochastic fractal search (SFS) algorithms are some of these methods. The AIS algorithm was proposed by Basu [40], in 2012, to solve the CHPED optimization problem. A comparison, which was carried out among the results of the AIS algorithm and those gained from the PSO and the EP algorithms, showed the superiority of the AIS, in terms of the obtained cost and speed of the process. In another optimal scheduling problem, the HSS was implemented in a model of fuel cell-CHP combined with the battery energy storage [41]. The SFS algorithm, which is inspired by the natural phenomenon of growth [42], was applied to the CHPED problem by Alomoush [43]. Using the SFS in a test system consisting of a conventional power generation unit, two CHP units, and a heat-only generation unit resulted in 9257.07 $ as the total cost of the plant.

According to the above studies, the genetic algorithms can be applied in various types of single-objective CHP optimization issues. This ability of the GAs to solve a wide range of optimization problems, such as optimal designing, sizing, and scheduling of CHP plants, converted them into robust methods. Other kinds of EAs, such as the DE, AIS, and SFS algorithms can achieve great results, in solving a common scheduling model of the CHPs, known as the CHPED problem.

2.2. Swarm Intelligence-Based Algorithms as Single-Objective for CHP

The swarm intelligence-based algorithms (SIs), as another category of the population-based meta-heuristic methods, could be successfully performed in optimization problems. These kinds of algorithms, inspired by the collective behavior of animals, find the best solution. The SI-based algorithms have been developed alongside the EAs [44].

- The Particle Swarm Optimization Algorithms

The original version of the particle swarm optimization (PSO) algorithm was introduced by Kennedy and Eberhart [45], in 1995. This algorithm is inspired by the social interaction of fish schooling and birds flocking. However, the standard version of the PSO has undergone many changes by some researchers, due to related problems. For example, a form of the PSO, the time-varying acceleration coefficients particle swarm optimization (TVAC-PSO), was used to solve the CHPED problem, by Mohammadi-Ivatloo et al. [46]. Additionally, Zeng et al. [47] used the chaotic search strategy, the time-variant acceleration coefficients, and the self-adaptive mutation operator in the PSO algorithm to solve a combined heat and power dynamic economic dispatch problem. In another CHPED optimization issue, the Gaussian random variables were added to the velocity term of the PSO algorithm to calculate the modified velocity and position of the particles in each iteration. This modified particle swarm optimization (MPSO) algorithm presented by Basu [48], achieved the global optimum through high population diversity caused by the Gaussian random variables.

The PSO algorithms have been applied to the problems that address the optimal scheduling of the CHP-based microgrids. These energy systems usually involve various types of energy sources, such as wind turbines, photovoltaic plants, cogeneration systems, and energy storage; some studies in this area considered the stochastic nature of these systems. Liu et al. [49] applied a multi-team particle swarm optimization (MTPSO) algorithm to minimize the total operating cost of a CHP-based microgrid. The presented MTPSO algorithm updated the velocity of each particle, more stably. Since the scheduling problems are complex nonlinear optimization models, Zeng et al. [50] presented an improved PSO algorithm, which incorporated a self-adaptive mutation scheme, time-variant parameters, and efficient constraint handling methods to minimize the total cost of a CHP-based steam power plant. In another economic dispatch problem of a multiple energy carriers system consisting of CHP plants, the TVAC-PSO algorithm was applied [51]. The cost-effective scheduling of three different on-grid hybrid CHP-based energy systems has been also achieved by applying the modified PSO algorithm [52–54]. Additionally, the adaptive PSO algorithm was used in a bi-level economic scheduling model of an integrated energy system, based on the power internet of things [55]. Liu et al. [56] minimized the coal consumption of a coal-fired CHP plant combined with power-to-heat devices using the PSO algorithm. They consider operation scheduling of the system to achieve their goal.

To guarantee the reliability and economic efficiency of microgrids (MG), applying and optimal sizing of the energy storage system (ESS) is necessary. Accordingly, Liu et al. [57] modeled an off-grid MG, which consists of distributed energy resources, a CHP plant, ESS, and electric vehicles, and used the PSO to obtain an optimal sizing of the ESS. Following the works conducted for modifying the PSO algorithms, a novel advanced modified particle swarm optimization (AMPSO) algorithm was presented by Neyestani et al. [58] to solve the CHPED problem. The results obtained by the study showed the superiority of the AMPSO over the TVAC-PSO algorithm. Another attempt for modifying the PSO method was carried out by Lashkar-Ara et al. [59]. They applied the self-regulation controls learning process, which made an improved version of the PSO named the SRPSO method to solve the CHPED problem. Additionally, an improved PSO algorithm, combined with a mutation operator, was used for finding the optimal combination and allocation of three types of CHP plants [60]. It should be stated that in most of the works focused on CHP plant optimization, these types of energy systems consisted of only one CHP unit. However, in a novel configuration, a large-scale CHP plant, composed of two CHP units and a thermal storage tank was modeled, and the PSO algorithm was used for optimization (Figure 4). The optimization achieved great results in minimizing coal consumption [61]. Additionally, a CHP plant with multiple CHP units and power-to-heat converters has been modeled and optimized by applying the PSO algorithm [62].

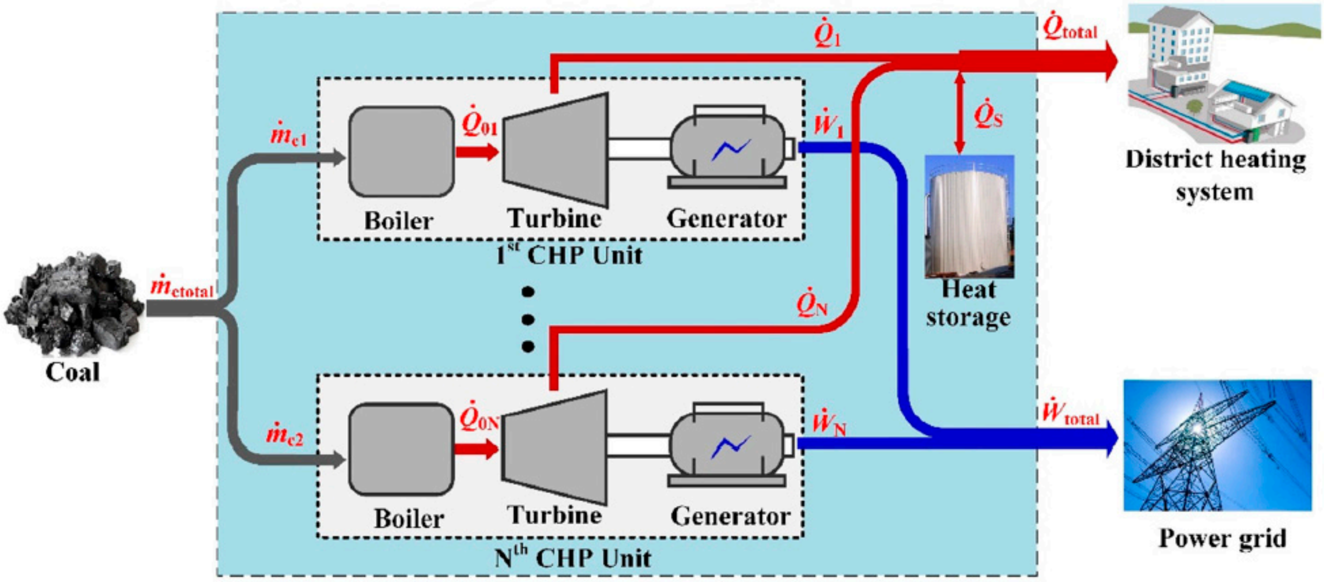

Figure 4. Configuration of a large-scale CHP plant composed of two CHP units and a thermal storage tank [61].

- The Cuckoo-inspiration Algorithms

The cuckoo search algorithm (CSA) [63], as an SI-based method, imitates the obligate brood parasitic behavior of some cuckoo species. In this algorithm, the solutions are generated via two stages, the Lévy flights, and the alien egg discovery. The CSA showed a great performance in a strategy, which was applied for optimizing a CHPED problem [64]. This strategy uses the techniques for handling equality constraints. The cuckoo optimization algorithm (COA), with the same inspiration as the CSA algorithm, was introduced by Rajabioun [65] in 2011. Mellal et al. [66], used the COA with the penalty function (PFCOA) for constraint handling in a CHPED problem in 2015. In another study, the COA was applied in a CHPED issue, considering the valve-point effect, the transmission loss, the heat-power dual dependency, and the capacity limits [67].

- The Whale Optimization Algorithm

The whale optimization algorithm (WOA), inspired by the social behavior of humpback whales, was presented by Mirjalili et al. [68], in 2016. This algorithm was applied to the common CHPED optimization problem, in 2017 [69]. In another study, in 2019, Massrur et al. [70] presented a novel optimal model of a grid-connected energy microgrid, by using the self-adaptive modified WOA (SMWOA). Additionally, an improved WOA (IWOA), applying the adaptive weights was proposed by Zhu et al. [71] to minimize the difference between the required electricity and the actual output from a grid-connected CHP plant.

- The Group Search Optimizer Algorithm

The group search optimization (GSO) algorithm is inspired by animals' searching behavior and their group-living theory. Two strategies inspired by animal foraging behavior including searching for food and collective movement toward food resources were used in this meta-heuristic algorithm. In each generation, three types of members are considered: the producer as the best member, the scroungers as the other group members, and the rangers as the remaining members. This algorithm was improved by Tarafdar-Hagh et al. [72] to better approach the global optimum point of a CHPED problem. Additionally, the classic GSO was applied in a CHPED problem by Basu [73]. In 2017, a modified version of the GSO (MGSO) was proposed by Davoodi et al. [74]. This modification was carried out by applying two adaptive scrounger and ranger strategies, to avoid trapping in poor local optima and give more diversity. The findings of the MGSO method were compared with those of the cuckoo optimization algorithm [75], and the MGSO showed a lower total cost than the COA.

- The Bee-Inspired Algorithms

The bee colony optimization (BCO) and the artificial bee colony (ABC) algorithms are the SI-based methods, inspired by the food foraging action of honeybees. The BCO, ABC and improved ABC (IABC) algorithms have been applied in the CHPED problems in [76–78], respectively. The results of implementing these algorithms in a test system showed a lower minimum cost and computational time of the IABC algorithm than the ABC and BCO. The test system consisted of two cogeneration units, four conventional thermal generators, and a heat-only unit. Additionally, the heat and power demands of the test system were reported as 150 MWth and 600 MWe, respectively [79]. The obtained results of the BCO, ABC, and IABC are shown in Table 1.

Table 1. The numeric results of the BCO, ABC, and IABC, implemented in a CHPED model *.

Applied Algorithm/Ref.	Total Cost (US$)	Computation Time (s)
BCO [76]	10,317	5.16
ABC [77]	10,314	4.98
IABC [78]	10,112	2.21

* Consists of four power-only units, two CHP units, and one heat-only unit.

- The Firefly Algorithm

The firefly algorithm (FA) is one of the SI-based algorithms, because of inspiration from the flash lighting behavior of fireflies to attract potential mates or prey. In 2012, an adaptive modified firefly algorithm was presented, to minimize the total operating cost of a CHP-based microgrid [80]. The ability of the FA to solve the CHPED problem was proved in a study by Yazdani et al. [81], in 2013. Additionally, in a scheduling optimization issue, a modified version of the FA (MFA) was applied by Bornapour et al. [82] to maximize the profit of fuel cell CHP-based microgrid with hydrogen storage. The MFA benefited from the mutation method to preserve the diversity of the population.

- Other Swarm Intelligence-based Algorithms

There are other SI-based algorithms to solve the CHPED optimization issue. For example, the ant colony search algorithm (ACSA), which imitates the real ants' behavior in finding the nearest food sources, was improved and used by Song et al. [83]. The other SI-based solvers for this issue, such as the difference brain storm optimization algorithm, the wild goats algorithm, and the modified bat algorithm were presented in [84–86], respectively. In another study, regarding optimal dispatching, the squirrel search algorithm (SSA) was suggested. That study modeled the solar and wind power sources incorporated with a CHP [87]. In 2020, the wild goats algorithm was applied by Jafari et al. [88] in an energy management approach, considered for a multi-microgrid. As another application of the SI-based methods, the grey wolf optimization (GWO) algorithm, in combination with three mutation strategies, was used in an optimal scheduling problem [89]. Additionally, Mahian et al. [90] achieved the best combination and allocating of a hybrid CHP plant by the GWO method. They considered minimization of the plant's total cost for selecting the proper combination. Additionally, another SI-based algorithm named the marine predators algorithm was presented by Shaheen et al. [91] to solve the CHPED problem. This algorithm showed great features in terms of efficiency, feasibility, and capability in achieving the optimal solutions for small, medium and large-scale plants.

The particle swarm optimization algorithms can be introduced as one of the most useful SI-based methods in solving the single-objective CHP optimization cases. As discussed before, various improvement strategies have been applied in the PSO process, by some researchers. The time-varying acceleration coefficients and self-adaptive mutation operators are the most efficient methods in this area. As in other SI-based methods, the cuckoo-inspiration algorithms, the whale optimization algorithms, the group search optimizer, the bee-inspired algorithms, and the firefly algorithms can be introduced as robust methods to solve the single-objective CHP issues. These algorithms, in the classic or modified forms, have been frequently applied in some CHPED optimization problems.

2.3. Human-Based Algorithms as Single-Objective for CHP

Since the human being has greater social intelligence and fitness ability than the insect colonies, the human-based algorithms are introduced as a new category of meta-heuristics [68]. These kinds of meta-heuristics are inspired by the behaviors and characteristics of human beings [92]. The harmony search algorithm (HSA), the teaching learning-based optimization algorithm (TLBO), the exchange market algorithm (EMA), and the social cognitive optimization algorithm (SCO) are discussed below.

- The Harmony Search Algorithm

The HSA, which was introduced first time in 2001 [93], determines the optimum value of the objective function by utilizing the concept of how the perfect state of harmony is found through an aesthetic estimation. The HSA was applied in the CHPED optimization issue in [94]. A modified HSA, appropriate for the economic dispatch (ED) problem, named the EDHS, was also applied in a CHPED problem [95]. The EDHS algorithm as the modified version of the HSA, achieved a lower minimum cost than the classical HSA. In 2012, Javadi et al. [96] solved the day-ahead generation scheduling of a CHP, by applying the HSA. They showed a satisfying performance of this algorithm in terms of effectiveness and fastness. Javadi et al. [97] solved a CHPED problem, in a comparative study, by applying the HSA and a mathematical method. The mathematical method had a problem of convergence and difficulty dealing with a huge number of decision parameters and inequality constraints; while the HSA converged to a good solution and overcame a huge number of decision parameters. It should be noted that both HSA and mathematical methods obtained equal values of the plant's total cost. Additionally, in 2019, Benayed et al. [98] developed an improved harmony search (IHS) algorithm that generated new solution vectors to enhance the convergence characteristics and accuracy to solve the CHPED problem. In the same year, Nazari-Heris et al. [99] used a novel multi-player harmony search (MPHS) method to solve the CHPED problem. The number of iterations in the MPHS algorithm, WOA, TVAC-PSO, and the RCGA-IMM is shown in Figure 5. As it is evident from the figure, the MPHS converges to a lower cost, in a less iteration number.

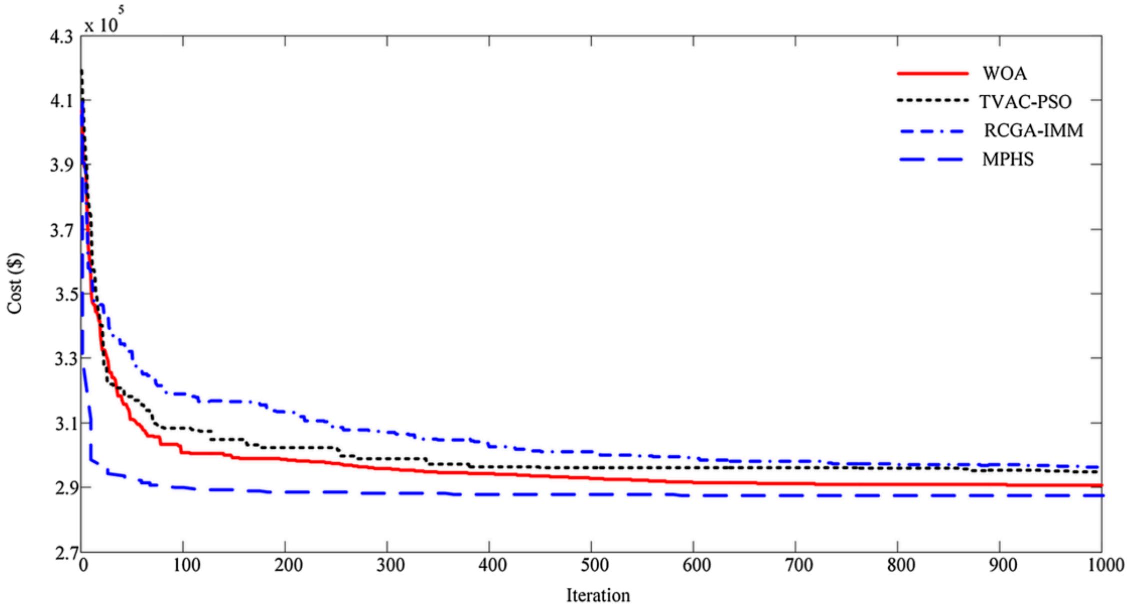

Figure 5. Comparison of the convergence characteristics of the MPHS algorithm and the other applied optimization algorithms to solve a CHPED case [99].

- The Teaching Learning-based Optimization Algorithm

The teaching learning-based optimization (TLBO) algorithm was introduced by Rao et al. [100] by inspiration from the teaching–learning process in the classroom, in 2011. Pattanaik et al. [101] modified this algorithm by adding the Gaussian random variables and applied it to a CHPED problem, in 2017. In another modification process carried out by Gong et al. [102], the students' diversity was increased. This increment caused a significant reduction in the possibility of premature convergence. This modified TLBO algorithm was applied to obtain a stochastic-based optimal energy management model for smart hybrid microgrids.

- Other Human-based Algorithms

The exchange market algorithm (EMA) is a human-based meta-heuristic method, because of inspiration from the shares trading style among the elite stockholders. This algorithm was applied to solve the CHPED case by Ghorbani [103] in 2016. As another human-based solver for the CHP optimization issues, the social cognitive optimization (SCO) algorithm can be introduced. The SCO, which is inspired by the mankind studying method [104] was combined with the tent map model, as a new algorithm named the TSCO for converging the CHPED issue [105]. The computation time of the SCO process was 0.673 s, while it was 0.535 s for the TSCO. So, it could be concluded that the tent map model, as a chaotic search strategy, would reduce the computation time of the SCO algorithm. Additionally, a novel meta-heuristic algorithm was introduced by Srivastava et al. [106], with inspiration from a game played in India. This algorithm named the Kho-Kho optimization algorithm accounted as a subcategory of the human-based meta-heuristics and was applied for a CHPED problem. Another human-based algorithm named heap-based optimizer was introduced by Ginidi et al. [107] for optimal dispatching of a large-scale CHP system to minimize the total fuel cost.

2.4. Physics-Based Algorithms as Single-Objective for CHP

The physics-based algorithms are known as another subcategory of the population-based meta-heuristics, by imitating the physical rules of the universe [68]. The charged system search algorithm (CSSA), the gravitational search algorithm (GSA), and the heat transfer search algorithm (HTS) are the physics-based methods that are discussed in this section. In 2013, Bahmani-Firouzi et al. [108] modified the CSSA by applying a self-adaptive learning framework (SALCSSA) to eliminate the probable preconvergence of local optima, population diversity lost, or slow processing of the CSSA. They used the modified CSSA to obtain an optimal dynamic economic dispatch of a CHP plant. In confirmation of another physics-based method in CHP optimization issues, the GSA was presented by Beigvand et al. [109] for the CHPED problem. The GSA showed a great capability in finding an optimal point with lower fuel cost and less computation time compared to the GA, RCGA, EDHS, HSA, PSO, TVAC-PSO, BCO, EP, and DE. Another physics-based method, the HTS algorithm, was also applied to solve the CHPED problem by Pattanaik et al. [110], in 2019.

2.5. Hybrid Meta-Heuristic Methods

The hybrid optimization techniques make an important section, in engineering issues. Combining the different optimization methods causes improvement in their performance and better designing and coding of optimization problems as well [111]. The hybridizing process can be conducted in three ways: combining the meta-heuristic algorithms, combining the meta-heuristic algorithms and machine learning programming methods, and combining the meta-heuristic algorithms and mathematical optimization methods.

- Combining the meta-heuristics methods

Arandian et al. [112] applied a hybrid shuffled frog leaping algorithm for stochastic economic locating and sizing a CHP-PV system integrated with energy storage. Beigvand et al. [113] developed a hybrid algorithm based on the GSA, to solve the CHPED problem. The presented algorithm was a time-varying acceleration coefficients-gravitational search algorithm-particle swarm optimization (TVAC-GSA-PSO). In 2018, the hybrid CSA-BA-ABC algorithm was obtained by combining the bat algorithm (BA) and the ABC algorithm, based on the chaotic-based self-adaptive (CSA) strategy. This algorithm was used as a solver for the CHPED problem by Murugan et al. [114]. This algorithm showed good convergence characteristics, because of inheriting the exploration abilities of the ABC and exploitation ability of the BA. The performance of the hybrid TVAC-GSA-PSO and hybrid CSA-BA-ABC algorithms was compared by considering a 48-unit CHP plant, as a particular test system [109]. This implementation had a total cost of 116,393.4034 $ and 115,770.3910 $, and the computation time was 6.63 s and 11.3455 s, with the TVAC-GSA-PSO and CSA-BA-ABC, respectively. Nevertheless, the CSA-BA-ABC showed a lower total cost but consumed more computation time than the TVAC-GSA-PSO.

To avoid the local optimum points that might take place in the PSO algorithmic process, three operators were adopted from the DE algorithm. This novel evolutionary PSO (E-PSO) algorithm was applied by Lorestani et al. [115], for optimal sizing of a CHP plant, incorporated with renewable energy sources and energy storage. Gu et al. [116] improved the weak characteristics of the biogeography-based optimization (BBO) algorithm by hybridizing the BBO and the SA algorithm (SABBO), for the economic dispatching of CHP plants. In a study carried out in 2019, the performance of the GA, PSO, and PSO-GA algorithms was compared for optimizing the economic dispatch of a CHP plant. It was shown that the PSO-GA algorithm obtained the best results [117]. Additionally, in an optimal scheduling problem, an evolutionary algorithm, the DE, and a swarm-based algorithm, the bird mating optimization (BMO), were combined by Bornapour et al. [118]. The studied model was a grid-connected microgrid including a fuel-cell CHP, wind turbines, and photovoltaic modules. In another hybridizing process, Hu et al. [119] used the PSO algorithm and the GA, simultaneously, for presenting an economic dispatch model of a wind-solar power-hydrothermal cogeneration system. Nasir et al. [120] used a hybrid FA and self-regulating PSO algorithm to solve the CHPED problem. They concluded that this algorithm exploited the strong points of FA and self-regulating PSO simultaneously. Additionally, a novel hybrid heap-based and jellyfish search algorithm were used by Ginidi et al. [121] in a CHPED optimization problem. This hybrid algorithm benefited from the explorative features of the heap-based algorithm and exploitative features of the jellyfish search algorithm.

- Combining the meta-heuristics and the machine learning programming

The opposition-based learning (OBL) algorithm, as a novel scheme for machine intelligence, is one of the most successful concepts for improving the search abilities of the population-based optimization algorithms to solve nonlinear problems. In this regard, some researchers have combined the meta-heuristic algorithms with the OBL technique. Roy et al. [122] proposed a hybrid algorithm, based on the TLBO, incorporated with the OBL (OTLBO), for a CHPED problem. Additionally, Niu et al. [123] applied the OBL in the harmony search algorithm with the arithmetic crossover operation to enhance the diversity of the solution. The opposition-based group search optimization (OGSO) algorithm (shown in Figure 6) was applied to a CHPED problem by Basu [124]. As is evident from the figure, at the first level, the initial members and the opposite members are generated. Then, by evaluating the fitness of the opposite member, the replacing operation is carried out. In the next stages, by choosing the relating members, producing and scrounging are performed. The numeric results showed that the OGSO reached a lower total cost than the obtained cost of the GSO. It should be noted that the OGSO consumed more computation time than the GSO. The advantages of the OBL algorithm are the improvement in convergence speed, the search process, and the achievement of high-quality solutions, through accounting for the current population and its opposite population at the same time.

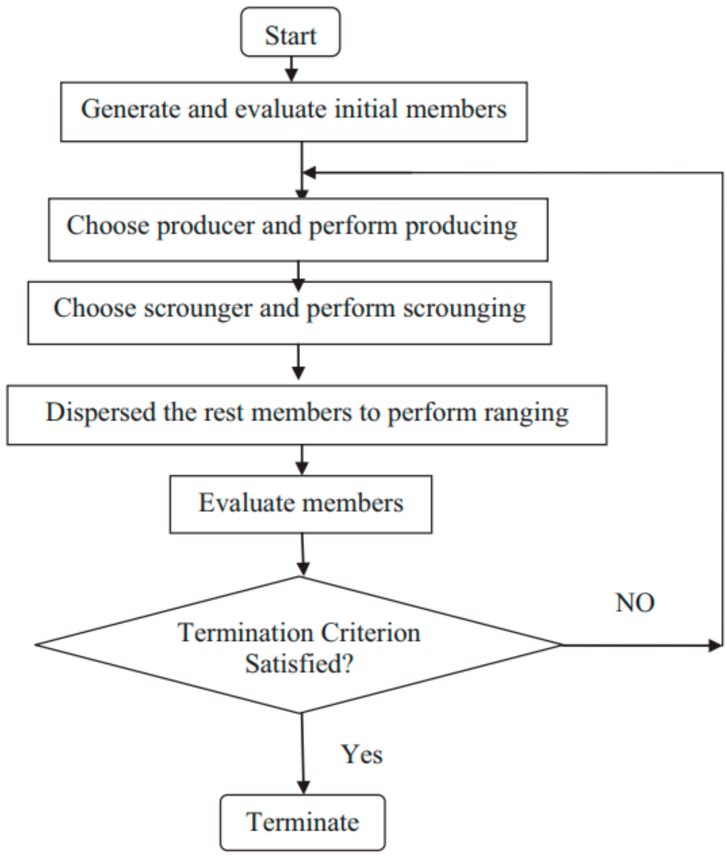

Figure 6. The general process of the OGSO algorithm [124].

- Combining the meta-heuristics and the mathematical programming methods

Mathematical programming can improve the ability of meta-heuristic algorithms in a variety of issues. There are significant numbers of papers in this area. In research work, by Moradi et al. [125], the uncertainties of a CHP and a boiler optimization model were considered through a fuzzy programming method. The PSO and the linear programming methods were applied for obtaining the optimal capacities of the presented model. Hosseini et al. [126] obtained the optimal placing and sizing of CHP plants, by applying the

PSO algorithm as a solver. Then, they applied the Monte Carlo method for simulating the effect of the stochastic nature of the power generation system on the optimal solution. As it could be understood from the literature, the mathematical methods are efficient solvers to handle the models' uncertainties. Wu et al. [127] scheduled a CHP-based microgrid using an improved PSO algorithm combined with the Monte Carlo simulation. Additionally, an optimization model based on the Stackelberg game was presented by Ma et al. [128] to manage the energy of a microgrid. The DE algorithm and the nonlinear constrained programming were chosen to solve this optimization model.

Another hybrid method was applied by Pazouki et al. [129] to achieve the best placing and sizing of CHP units in multi-carrier energy networks. The mixed integer linear programming model and the CPLEX Optimization Studio [130] were used to solve different scenarios. Then, those with lower profits were eliminated, and the genetic algorithm was applied to determine the best scenario. In 2017, Elsido et el. [131] proposed a two-level optimization process for determining the optimal design and scheduling of CHP plants. As shown in Figure 7, the optimal design of the units was carried out at the first level (the upper level), by an evolutionary algorithm, while the optimal scheduling was obtained at the lower level by the commercial mixed integer linear programming (MILP). The total operating cost (TOC), obtained from the lower level, was transferred to the total annual cost (TAC) as the objective function. The combination of meta-heuristics and mathematical methods has been used in the CHPED issues as the significant optimization problems of the CHP plants. In this field, an integrated technique was applied by Narang et al. [132], and the civilized swarm optimization (CSO) algorithm was selected as a global search method, and Powell's Pattern Search (PPS) was applied as a local search method.

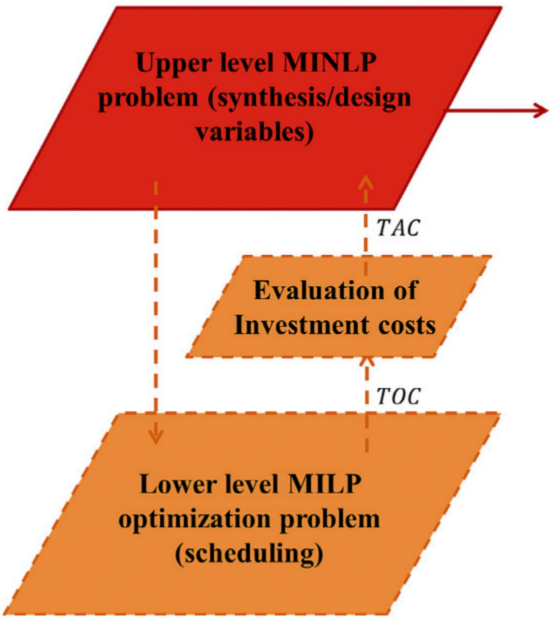

Figure 7. Scheme of the two-level optimization process. The TOC, minimized at the lower level, transferred to the TAC, minimized at the upper level [131].

Some other works have proved the high ability of the mathematical methods in handling the uncertainties of the considered models. For example, to consider the uncertainties of a CHP plant combined with a wind power plant, a novel chance-constrained programming model and a two-stage hybrid method based on the SQP and the GA were introduced [133]. Additionally, solving a non-deterministic optimal scheduling model of a dual-mode CHP was carried out through the combination of the binary successive approximation method and the civilized swarm optimization algorithm [134]. In another paper, a two-level hybrid method, including the PSO and SQP, was applied by Eladl et al. [135] to optimize a stochastic model of a power system. The energy system consisted of CHP units, a photovoltaic module, a wind turbine, and battery energy storage.

Based on the reviewed papers in the field of the hybrid method, the combination of the meta-heuristic algorithms is usually carried out to overcome the shortcomings of the methods and obtain a better optimal solution. The usage of the machine learning programming methods in combination with the meta-heuristics, not only accelerates the optimization process but also increases the accuracy of the final answer. The opposition-based algorithm can be introduced as an efficient method in this area. As the third way of combination, applying mathematical programming alongside the meta-heuristics can overcome the stochastic characteristics of the optimization models in a good way. Regarding this matter, the PEM, the fuzzy programming, and the Monte Carlo simulation are accounted for as effective mathematical methods.

According to the literature, the single-objective CHP optimization issues can be classified into three main categories, including scheduling, designing, and sizing issues. The economic dispatching of the CHP plants, known as the CHPED optimization problem, is presented as a separate category in this paper. This is because of the wide applications of the CHPED in various studies. Accordingly, the most significant single-objective CHP optimization problems reported in the literature are presented in four categories including scheduling, designing, sizing, and economic dispatching, in Tables 2–5, respectively. The objective function of the CHPED problem is total fuel cost; the relevant column in Table 5 is not provided. Additionally, the column of the energy system is not provided in Table 5 because it is considered a fixed CHPED test system.

Table 2. Single-objective scheduling issues of CHP energy systems.

Applied Algorithm	Energy System	Objective Function	Authors/Ref.
GA	Solar-fossil fueled CHP plant combined with thermal storage and dispatching	Minimization of energy cost	Abdelhady et al. [29]
NSGA-II	Grid-connected CHP-based microgrid	Minimization of the total cost	Shang et al. [30]
GA	Grid-connected hybrid solar-wind-hydrogen CHP	Minimization of total cost	Maleki et al. [31]
SADE	Grid-connected fuel cell-based CHP	Minimization of the total cost	Venkatakrishnan et al. [35]
IDE	Integrated energy system with CHP, photovoltaic and energy storage	Minimization of the operation cost	Wang et al. [37]
MTPSO	CHP-based microgrid	Minimization of the total operating cost	Liu et al. [49]
IPSO	CHP-based steam power plant	Minimization of the total cost	Zeng et al. [50]
PSO	Large-scale CHP plant, with two CHP units and a thermal storage tank	Minimization of coal consumption	Lai et al. [61]
SMWOA	grid-connected CHP-based microgrid	Minimization of the day-ahead operating cost	Massrur et al. [70]
MFA	fuel cell CHP-based microgrid with hydrogen storage	Maximization of the profit	Bornapour et al. [82]
SSA	Solar and wind power sources incorporated with a CHP	Minimization of the total cost	Basu [87]
Wild Goats	CHP-based multi-microgrid	Maximization of the profit	Jafari et al. [88]
Modified TLBO	Smart hybrid microgrids	Minimization of the total cost	Gong et al. [102]
BMO-DE	Grid-connected microgrid with fuel-cell CHP, wind turbine, and photovoltaic modules	Maximization of the profit	Bornapour et al. [118]
PSO-GA	Wind-solar power-hydrothermal cogeneration system	Minimization of the total cost	Hu et al. [119]
Improved PSO with the Monte Carlo	CHP-based microgrid	Minimization of the total cost	Wu et al. [127]
DE with Nonlinear Constrained Programming	CHP-based microgrid	Maximization of the profit	Ma et al. [128]
PSO and SQP	CHP with photovoltaic, wind turbine, and battery	Maximization of the social welfare	Eladl et al. [135]

Table 3. Single-objective designing issues of CHP energy systems.

Applied Algorithm	Energy System	Objective Function	Authors/Ref.
GA	Typical gas-turbine CHP plant	Minimization of the total cost	Ahmadi et al. [19]
GA	diesel engine-based CHP system	Minimization of the total cost	Mohammadkhani et al. [20]
GA	Fuel cell based micro-CHP	Maximization of the electrical efficiency	Arsalis et al. [21]

Table 4. Single-objective sizing issues of CHP energy systems.

Applied Algorithm	Energy System	Objective Function	Authors/Ref.
Fit-problem GA	Gas turbine CHP plant	Maximization of the annual worth	Ferreira et al. [24]
GA	Building-integrated CHP plant	Minimization of the daily energy cost	Yu et al. [25]
PSO	Off-grid MG with CHP, ESS, and electric vehicles	Minimization of the total cost	Liu et al. [57]
GWO	Hybrid CHP plant	Minimization of the total cost	Mahian et al. [90]
Hybrid shuffled frog leaping algorithm	CHP-PV plant integrated with energy storages	Maximization of the profit	Arandian et al. [112]
E-PSO	CHP plant with renewable energy and energy storage	Minimization of the total annual cost	Lorestani et al. [115]
PSO and linear programming	Grid-connected boiler and CHP plants	Maximization of the net present value	Moradi et al. [125]
PSO and Monte Carlo	CHP plants	Maximization of the benefit to cost ratio	Hosseini et al. [126]
Mixed integer linear programming and GA	CHP units in multi-carrier energy networks	Maximization of the profit	Pazouki et al. [129]

Table 5. Economic dispatching issues of CHP energy systems (CHPED optimization issues).

Authors	Applied Algorithm	Ref.
Haghrah et al.	RCGA-IMM	[26]
Zou et al.	IGA-NCM	[27]
Basu	DE	[33]
Jena et al.	DEGM	[36]
Basu	AIS	[40]
Mohammadi-Ivatloo et al.	TVAC-PSO	[46]
Zeng et al.	IPSO	[47]
Basu	MPSO	[48]
Neyestani et al.	AMPSO	[58]
Lashkar-Ara et al.	SRPSO	[59]
Mellal et al.	PFCOA	[66]
Basu	GSO	[73]
Davoodi et al.	MGSO	[74]
Yazdani et al.	FA	[81]
Song et al.	ACSA	[83]
Javadi et al.	HSA	[97]
Benayed et al.	IHS	[98]
Nazari-Heris et al.	MPHS	[99]
Pattanaik et al.	TLBO	[101]
Ghorbani	EMA	[103]
Sun et al.	TSCO	[105]
Srivastava et al.	Kho-Kho	[106]
Bahmani-Firouzi et al.	SALCSSA	[108]
Beigvand et al.	GSA	[109]
Pattanaik et al.	HTS	[110]
Beigvand et al.	TVAC-GSA-PSO	[113]
Murugan et al.	CSA-BA-ABC	[114]
Gu et al.	SABBO	[116]
Nasir et al.	FA-PSO	[120]
Roy et al.	OTLBO	[122]
Basu	OGSO	[124]
Narang et al.	CSO and PPS	[132]

The statistical study of the presented optimization issues shows the largest share of the CHPED problem, among the other optimization cases. As shown in Figure 8, the CHPED optimization problems, the other CHP scheduling issues, the CHP optimal sizing, and the optimal designing issues have 53%, 29%, 15%, and 3% of sharing among the studies, respectively. According to the obtained results, the CHPED problem can be selected, as the most useful single-objective CHP optimization issue. Thus, in order to pay more attention to this matter, the numeric results of the CHPED problem solved by different algorithms, are presented and compared in Table 6. The results are based on a specified test system composed of a conventional power generation unit, two CHP units, and a heat-only generation unit. The considered constraints of each presented model are also mentioned in the table. Presentation of this subject is important, because of the effect of different constraints on the total cost of the energy system.

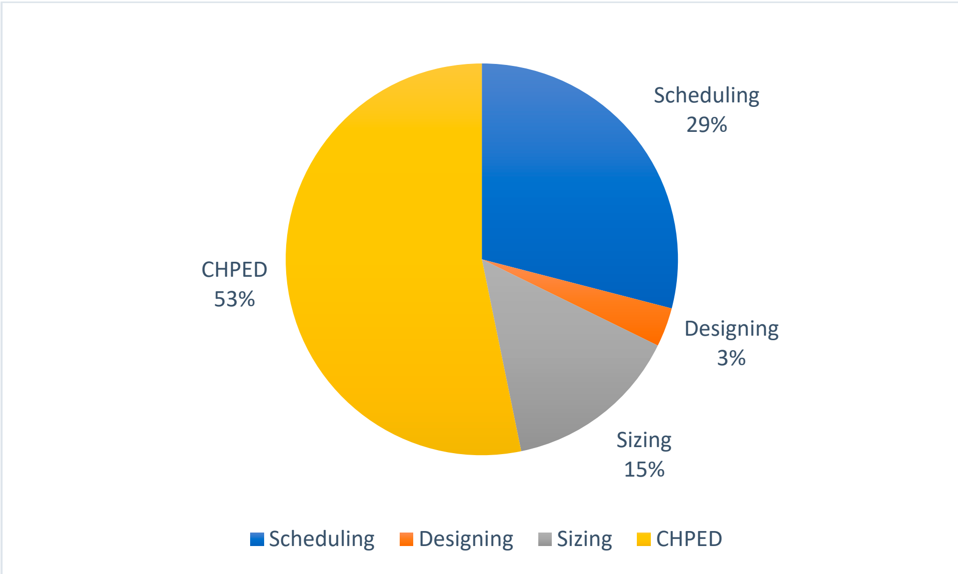

Figure 8. Sharing of the single-objective CHP optimization issues in four categories.

Table 6. The numerical results of implementing different algorithms in a CHPED optimization model *.

Applied Algorithm/Ref.	Total Cost (US$)	Computation Time (s)	Model Constraints
RCGA-IMM [26]	9257.075	NA	Heat and power demands, Capacity limits, Valve point effect, Transmission loss
IGA-NCM [27]	9257.075	NA	Heat and power demands, Capacity limits
DEGM [36]	9235.1032	1.0827	Heat and power demands, Capacity limits, Valve point effect
SFS [43]	9257.07	3.78	Heat and power demands, Capacity limits
TVAC-PSO [46]	9257.07	1.33	Heat and power demands, Capacity limits, Valve point effect, Transmission loss
SRPSO [59]	9257.07	0.62	Heat and power demands, Capacity limits, Valve point effect, Transmission loss
CSA [64]	9257.07	0.59	Heat and power demands, Capacity limits, valve point effect, transmission loss
PFCOA [66]	8440.50	NA	Heat and power demands, Capacity limits
GSO [73]	9236.0716	1.3705	Heat and power demands, Capacity limits, valve point effect
FA [81]	9257.10	NA	Heat and power demands, Capacity limits
ACSA [83]	9452.20	NA	Heat and power demands, Capacity limits
HSA [94]	9257.07	NA	Heat and power demands, Capacity limits

Table 6. *Cont.*

Applied Algorithm/Ref.	Total Cost (US$)	Computation Time (s)	Model Constraints
EDHS [95]	8606.07	NA	Heat and power demands, Capacity limits
IHS [98]	9179.5	NA	Heat and power demands, Capacity limits
EMA [103]	9257.07	0.9846	Heat and power demands, Capacity limits. Valve-point effect, Transmission loss
TSCO [105]	9257.07	0.535	Heat and power demands, Capacity limits, transmission loss
SCO [105]	9257.07	0.673	Heat and power demands, Capacity limits, transmission loss
HTS [110]	9256.95	1.38	Heat and power demands, Capacity limits. Valve-point effect, Transmission loss
SABBO [116]	9257.1	NA	Heat and power demands, Capacity limits
OGSO [124]	9290.5459	1.7309	valve point effect and prohibited operating zones of conventional thermal generator
GSO [124]	9291.2717	1.5273	valve point effect and prohibited operating zones of conventional thermal generator
CSO-PPS [132]	9257	0.56	Heat and power demands, Capacity limits, Valve point effect, prohibited operating zones, transmission loss

* The CHPED model consists of a power-only unit, two CHP units, and a heat-only unit.

Based on Table 6 the different algorithms obtained a range of costs, from 8440.50 $ to 9452.20 $. The lowest cost belongs to the PFCOA algorithm, while the highest cost belongs to the ACSA algorithm. The EDHS algorithm has also been an effective solver in the CHPED problems, by obtaining an 8606.07 $. The run speed of the algorithms to solve optimization problems is also an important criterion for engineers in this field. In solving the CHPED problems, the TSCO, CSO-PPS, and CSA algorithms show an excellent processing speed in comparison with the other algorithms.

3. Multi-Objective Algorithms for CHP Optimization

Since most real-world issues involve the simultaneous optimization of several objectives, multi-objective optimization is applied for optimizing several objective functions, simultaneously, with a number of inequality or equality constraints. Unlike single-objective optimization, which obtains one optimal solution, multi-objective optimization gives rise to a set of optimal solutions. These solutions are known as the pareto-optimal solutions.

3.1. Evolutionary Algorithms

The EAs have been widely used in multi-objective optimization problems because their natural characteristics are appropriate for these issues.

- Genetic Algorithm

To deal with the characteristics of a multi-objective optimization issue, the non-dominated sorting procedure as a ranking selection method was applied in the genetic algorithm that created the non-dominated sorting genetic algorithm (NSGA) [136]. Later, the NSGA was modified to a faster and more reliable algorithm, as the NSGA- II by using the crowding distance as a second-order sorting criterion [137]. By applying the NSGA- II, a multi-objective optimal design of a micro-CHP gas turbine was carried out by Yazdi et al. [138]. They considered the exergy efficiency, the total production cost, and the CO_2 emission of the plant, as the objective functions. In another work, by Ganjehkaviri et al. [139] a diesel engine-based CHP was optimally designed considering the system's exergy efficiency and the total cost as the objective functions. Additionally, similar objective functions were defined by Sanaye et al. [140] to optimize a hybrid solid oxide fuel cell and micro gas turbine CHP plant. Since maximizing the total exergy efficiency and minimizing the total cost of the system are in contrast with each other, the pareto frontier was obtained, as shown in Figure 9. Based on the figure, point P shows the final optimum point. After obtaining the pareto frontier, in order to select a final optimal point of the pareto frontier, the technique for order of preference by similarity to the ideal solution (TOPSIS) method as a decision-maker was applied. In the TOPSIS method, the two ideal and non-ideal solutions were obtained. The best solution was then selected from the pareto frontier based on the geometric shortest distance and longest distance from the ideal point and non-ideal point, respectively. The NSGA- II was also applied in a multi-objective optimization process for an integrated energy system consisting of biomass gasification, a solid oxide fuel cell, and a micro gas turbine CHP [141].

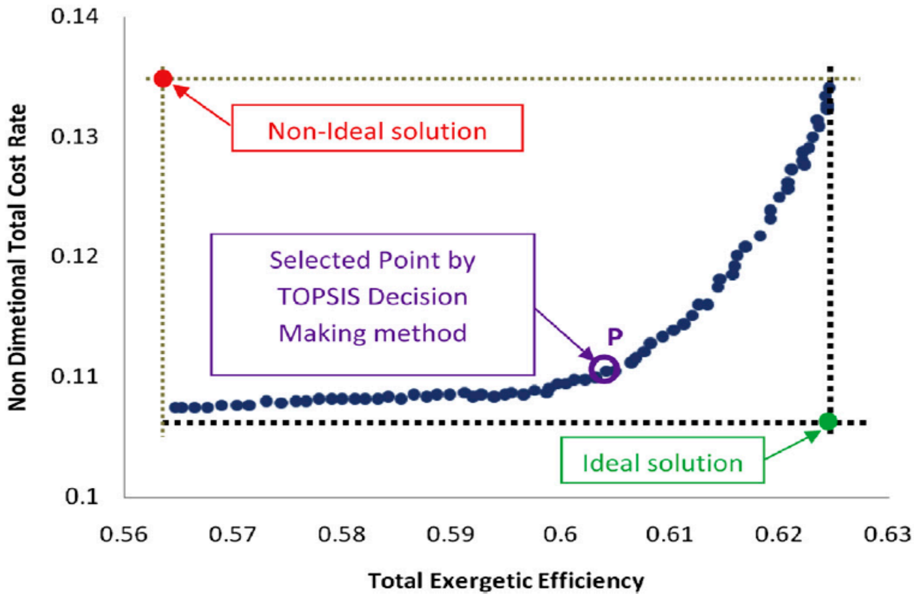

Figure 9. Selecting the optimum point from pareto frontier, representative of the best compromise, between the total cost and total exergetic efficiency of CHP plant, using TOPSIS decision making method [140].

Following the research works in the multi-objective optimal designing of CHPs, a fuel cell based micro CHP plant was optimized and the best trade-off between the total cost and the net electrical efficiency of a CHP plant was achieved as the pareto frontier by Haghighat-Mamaghani et al. [142]. In another multi-objective optimal designing issue, in 2016, a gas turbine-based CHP cycle integrated with low-energy buildings was simulated and optimized by a genetic-based algorithm [143]. In another optimal designing problem solved by the NSGA- II, Lee et al. [144] targeted the minimization of total cost and total environmental impacts of a wastewater treatment plant integrated with a CHP plant. The efficiency of the components, the temperature differences in the heat exchangers, and the pressure ratio of the compressor and the gas turbine were the design variables. Additionally, a combination of the CHP and heat pump (CHP-HP) was optimally designed for the purpose of primary energy saving, CO_2 emission reduction and annual expense saving by Li et al. [145]. The optimal values for these objective functions were obtained as 23.24%, 35.13% and 21.93%, respectively. In another work, two types of geothermal-fueled CHP plants were proposed and modeled by Ebadollahi et al. [146]. The modeling was carried out based on three objective functions including energy and exergy efficiencies and the total production cost of the plants. After optimizing by the GA, the best design solution was obtained by weighing each function. The multi-objective optimal design was also studied in [147,148] for various models of highly efficient combinations of CHP plants that were solved by the NSGA-II. The robustness of the GA was proved in a comparative study among the GA, bee colony and searching algorithms. The GA reached 0.0754 $/kWh of generation cost, 39.42% energy efficiency, and 85.42% exergy efficiency for a CHP plant [149]. Costa et al. [150] presented a model of a syngas engine-based CHP plant and optimized it by the GA to achieve a high-efficiency and low-emission design. In another optimal design issue, Kazemiani-Najafabadi et al. [151] considered the rate of carbon emissions, exergy efficiency, and payback period as the objective functions and applied the GA to solve the problem. The multi-objective GA was used by Li et al. [152] in the optimization process of cogeneration proton exchange membrane fuel cell. Three objectives were considered in this study including system efficiency, power density, and oxygen distribution uniformity on the cathode catalyst layer. Mehregan et al. [153] applied the GA to optimize a CHP plant with two prime movers. The objective functions were minimizing the fuel consumption and plant emissions and maximizing the efficiency of the system.

The combined heat and power economic emission dispatch (CHPEED), as another multi-objective optimization issue, determines a plant's power and heat production; while the system's production cost and emission level could be optimized simultaneously. In such matters, the power and heat demand and the other constraints must be met. The NSGA-II was applied to solve the CHPEED model, by Basu [154], in 2013. The heat-power feasible operation region of the CHP unit is shown in Figure 10. Implementing the NSGA-II in a test system [79] consisting of four thermal generators, two CHP units, and a heat-only unit obtained 13,433.19 $, and 25.8262 Kg, as the best tradeoff between minimum total cost and total emission of the plant. In another paper, the multi-objective optimal dispatching was obtained by Eladl et al. [155] for an energy hub, including various components, such as renewable energy resources, and a CHP plant. In the problem that aimed at the maximization of social welfare and the minimization of CO_2 emissions, a penalty factor was used to convert the emission values to emission cost and change the problem into a single-objective one.

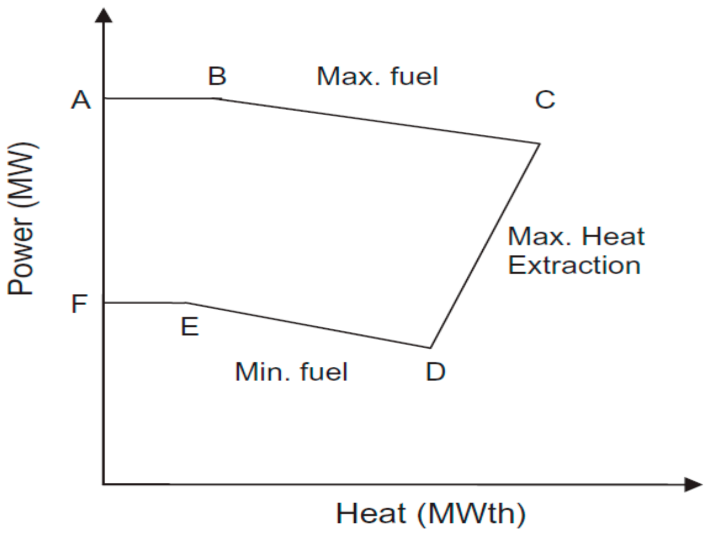

Figure 10. Heat-power feasible operation region for a CHP unit, considered for the CHPEED problem [154].

As another kind of CHP multi-objective issue, an optimal planning problem of a CHP-based microgrid was solved by Zidan et al. [156,157]. Two objective functions, including the total cost and the carbon dioxide emissions were considered and minimized, based on the genetic algorithm. In this planning issue, the best rating of the power and heat generation from each unit of the microgrid was obtained for four considered configurations of the microgrid and the best combination was selected. Assaf et al. [158] obtained the optimal sizing of a PV-CHP plant with a hot water storage tank to satisfy three objective functions. The decision variables in this problem were the power generation of the PV plant, electrolyzer, and fuel cell, the capacity of the hydrogen tank, the volume of the hot water storage tank, and the area of the solar collector. In another CHP sizing issue, Pujihatma et al. [159] compared the performance of the NSGA-II method with the goal attainment algorithm, as a deterministic method. The presented CHP system was fueled by petroleum gas and wet gas, in field gas utilization matter. The two methods gave an almost similar pareto front, according to the three objective functions, including the total fuel cost, the gas turbine reliability, and the pipeline integrity.

- Other Evolutionary Algorithms

The DE algorithm can be adapted as a solver for bi-objective economic emission load dispatch (EELD) problems. In an optimal scheduling issue, for a CHP-based microgrid, with economic and environmental purposes, the DE algorithm was used by Basu [160]. The DE algorithm showed faster processing than the PSO algorithm. The EELD problem for a CHP plant, known as the CHPEED issue was solved by Alomoush [161]. This optimization issue applied the SFS algorithm and the fuzzy satisfying method as a decision maker for selecting the best solution from the pareto set. Alomoush [162] also used different meta-heuristic methods to solve the economic and emission dispatching of a CHP-based microgrid. The SFS algorithm obtained the best compromise solution. In another work, Sun et al. [163] applied the indicator and crowding distance-based evolutionary algorithm (IDBEA) to achieve the best results for the CHPEED issue. In this study, the SFS method achieved the lower minimum cost, while the IDBEA obtained the lower emission level. Fan et al. [164] applied the sunflower optimization algorithm in a multi-objective optimal sizing problem of fuel cell-based CHP plants with three different types of heat pumps.

Based on the mentioned papers, the genetic algorithms as the largest group of EAs, apply the fitting strategies for multi-objective CHP optimization issues, in a good way. The NSGA-II is a good example in this area, which obtains high-quality solutions for CHP problems. Two other evolutionary algorithms, the DE and the SFS are effective methods in solving CHP matters, with more than one objective function. It should be noted that the EAs were mostly applied in the optimal designing problems of the CHP plant.

3.2. Swarm Intelligence-Based Algorithms

As the good performance of the swarm intelligence-based algorithms was discussed in the "single-objective" chapter, these methods could be successfully performed in the multi-objective optimization issues, as well.

- Particle Swarm Optimization Algorithm

The PSO algorithm was used by Zhao et al. [165] in an optimal designing problem to achieve the maximum values of exergy and electrical efficiencies. So, the mathematical model of a CHP plant, based on compressed air energy storage and a humid air turbine was formulated. The combination of the binary PSO and PSO methods was presented by Anand et al. [166] to solve a scheduling problem. This combined algorithm was presented to consider the unit status and explore some solutions for the multi-objective scheduling of a dual-mode CHP plant (Figure 11). Optimal scheduling of a dual-mode CHP plant was also solved by the binary PSO combined with the priority list method (PL) [167]. In a scheduling issue, Zeng et al. [168] used the demand response program (DRP) to model an MG. Then, they used an adaptive PSO algorithm to minimize the cost and emission of the MG. In a comparative study as a bi-objective optimal design of a CHP plant, the PSO showed a better convergence time than the GA [169]. In another design issue, the optimal design variables of a CHP plant composed of a supercritical CO_2 recompression Bryton cycle and an absorption heat pump were determined by the PSO algorithm [170]. In another study, the optimal locating and sizing of a CHP plant was obtained by Naderipour et al. [171], in a two-stage optimization process by the PSO. This process considered the minimization of the power loss, minimization of the energy not-supplied, and improvement of the voltage profile. In a comparative study by Nondy et al. [172], four metaheuristic algorithms including the PSO, the GA, the simulated annealing (SA), and the HS were applied in the thermoenvironomic optimization of a gas turbine-based CHP plant. In this research, the PSO algorithm showed the best performance.

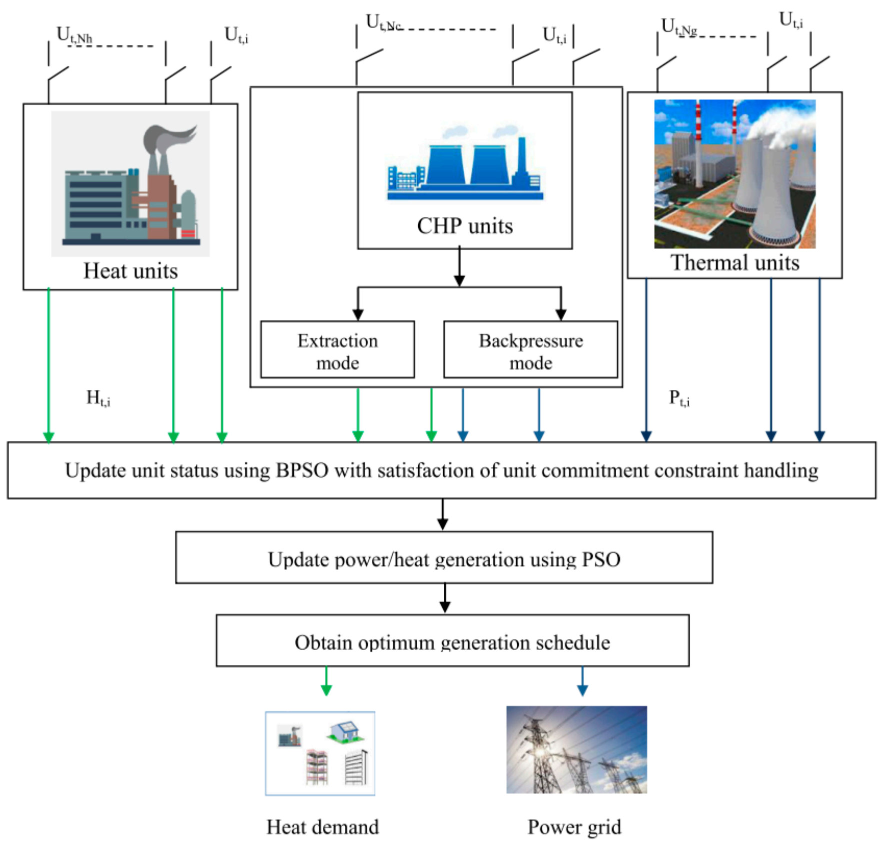

Figure 11. The process of optimal scheduling of a dual-mode CHP plant, with thermal and heat units, solved by combination of the binary PSO and PSO methods [166].

- Grey Wolf Optimization Algorithm

Jayakumar et al. [173,174] showed the good performance of the GWO algorithm in obtaining feasible and high quality solutions for the multi-objective dispatch of a CHP. They also modeled the CHPEED problem, considering both static and dynamic load conditions, and applied the GWO for this purpose [175]. The obtained results from this study were exactly similar to [174]. In another paper, a novel version of the GWO was developed by modifying the direction of the wolves, and utilization of the non-dominated sorting and crowded distance calculation. This algorithm was applied to solve the economic and environmental dispatch of the CHP plants [176].

- Other SI-based Algorithms

There are some other SI-based methods that are appropriate for solving the multi-objective CHP optimization cases. The FA method is one of these methods that was improved by adding the mutation operator into the optimization process to keep the population diversity. This improved FA was used by Bornapour et al. [177] to optimize a stochastic scheduling model of a CHP-based microgrid. Additionally, the fuzzy method was applied to select the best compromise solution, considering three objectives (Figure 12). In another study, He et al. [178] applied the multi-objective bacterial colony chemotaxis algorithm (MOBCC), for the economic and environmental scheduling of a CHP-based microgrid. In this optimization process, the TOPSIS method was used to determine the final solution. Yang et al. [179] presented an improved version of the SI-based collective animal behavior (ICAB) algorithm that utilized the chaos theory and the Levy flight method. The ICAB algorithm obtained the optimal design for a fuel cell-based CHP plant. Regarding the other applications of the SI-based methods in the CHP multi-objective issues, the WOA combined with the chaos theory can be introduced. This algorithm was applied in an economic and environmental dispatching problem of a wind turbine-CHP plant [180].

Another SI-based algorithm to solve the multi-objective optimization problem of CHP systems was presented by Cao et al. [181], in 2021. This multi-objective method was the Bat optimization algorithm that was used to optimize an innovative biomass gasifier system for combined heat and power production. This algorithm showed better results than the conventional multi-objective optimization methods. The total product cost and annual emission were reduced significantly after the optimization process.

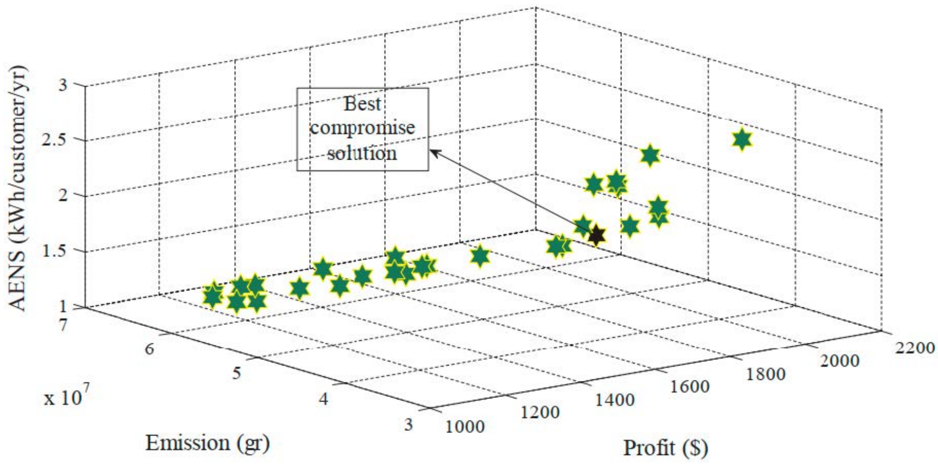

Figure 12. Selecting the best compromise solution, considering the best values for the market profit, total emission production, and average energy not supplied of a CHP-based microgrid [177].

It is understood from the literature that the SI-based methods have been highly applied in optimal scheduling issues. The PSO algorithm has been mostly applied in these kinds of optimization issues, but less in designing and sizing optimization issues. The GWO algorithm can be introduced as the second widely-used SI-based algorithm in multi-objective issues. This algorithm is a suitable solver for multi-objective scheduling problems. The firefly, BCC, collective animal behavior, and the whale optimization algorithms are the other useful methods for the multi-objective CHP issues.

3.3. Hybrid Metaheuristics Methods

A calculation algorithm was coupled with a multi-objective genetic algorithm to obtain the optimal configuration of a CHP plant [182]. As another mathematical method, considering the stochastic characteristics of CHP models, Shaabani et al. [183] applied the Monte Carlo method in combination with the TVAC-PSO. A calculation algorithm was coupled with a genetic algorithm, to obtain the optimal sizing of an on-grid CHP system. The optimization considered the maximum value for the primary energy saving, and the minimum value for the payback period [184].

As another type of the hybrid method, the combination of the meta-heuristics can be introduced. Azizipanah-Abarghooee et al. [185] proposed a hybrid method, that benefited from the characteristics of the modified Cuckoo search algorithm and the differential evolution (MCSA-DE). This hybrid method optimized a stochastic scheduling model of CHP-thermal-wind-photovoltaic units, based on chance-constrained programming. Another combination of meta-heuristic algorithms was presented by Dolatabadi et al. [186] to eliminate some flaws of the weighted vertices-based optimizer (WVO) algorithm. This combination was made by implementing the PSO algorithm. The WVO-PSO was implemented in a CHPEED problem. Nourianfar et al. [187] applied the TVAC-PSO algorithm in combination with the non-dominated sorting method, alongside the EMA, in a hybrid route. This hybrid algorithm obtained the economic and environmental dispatching of the CHP plant, in two static and dynamic modes. The combination of the NSGA- II and multi-objective PSO algorithms (NSGA II-MOPSO) was presented to solve a CHPEED model in [188]. By comparing the results of the NSGA II-MOPSO with those of the WVO-PSO, the WVO-PSO algorithm could be introduced as a better hybrid algorithm for the CHPEED issues. As previously discussed, the chaotic opposition-based learning strategy could improve the performance of the meta-heuristic algorithms. Regarding this issue, Sundaram [189] implemented this machine intelligence method in a multi-objective multi-verse optimization (MMVO) algorithm, to solve the CHPEED problem. A hybrid multi-objective algorithm as the combination of GWO algorithm and artificial neural network was proposed by Mushavarati et al. [190] to optimize a cogeneration biomass gasification plant. The GWO algorithm was applied to maximize the exergy efficiency and minimize the overall cost. On the other hand, the artificial neural network was used to improve the processing speed and decrease computational time.

3.4. Other Multi-Objective Meta-Heuristic Algorithms

The self-adaptive charged system search algorithm (SACSS) as a physics-based solver was used for optimal locating and sizing of a stochastic model of a fuel cell CHP plant. This model, which formulated random values of the input variables, was converted to some deterministic problems through some scenario-based methods [191]. As the other meta-heuristic methods to solve the CHPEED optimization issues, the multi-objective line-up competition algorithm (MLCA) was presented by Shi et al. [192] and the θ-dominance based evolutionary algorithm (θ-DEA) was proposed by Li et al. [193]. The MLCA and θ-DEA showed good performance in obtaining low emission levels in the CHP system. Pourghasem et al. [194] used the EMA to solve the stochastic dynamic reliable economic emission dispatching model of a renewable CHP-based microgrid. The weighted sum and fuzzy methods were selected for determining the final optimal solution. Keyhanasl et al. [195] proposed the modified TLBO algorithm to achieve the optimal energy flow of an integrated energy system that caused the minimization of operational energy cost, electrical losses and power flow imbalances.

Tables 7–10 present the multi-objective optimization models of the CHPs, studied in the literature, in four categories. The classification is similar to the single-objective chapter and includes the scheduling, designing, sizing, and CHPEED issues. Although the CHPEED is a subcategory of the scheduling issues, due to its high application in multi-objective CHP optimization studies it has been considered as a separate category in this paper.

Table 7. Multi-objective scheduling issues of CHP energy systems.

Applied Algorithm	Energy System	Objective Functions	Authors/Ref.
GA	Energy hub including renewable energy and CHP	Maximization the social welfare, minimizing the CO_2 emission	Eladl et al. [155]
DE	CHP-based microgrid	Minimization the total cost and total emission	Basu et al. [160]
Binary PSO	Dual-mode CHP plant	Maximizing the profit, minimizing the emissions	Anand et al. [166]
Adaptive PSO	CHP-based microgrid	Minimization of the cost and emission	Zeng et al. [168]
FA	CHP-based microgrid	Maximizing the profit, minimizing the total emission	Bornapour et al. [177]
MOBCC	CHP-based microgrid	Minimizing the economic and environmental costs	He et al. [178]
MCSA-DE	CHP-thermal-wind-photovoltaic units	Minimizing the cost, maximizing the probability of meeting the target cost	Azizipanah-abarghooee [185]
EMA	renewable CHP-based microgrid	Minimizing the total cost and emission level of the plant	Pourghasem et al. [194]
Modified TLBO	Integrated energy system	Minimizing the energy cost, electrical loss and power flow imbalances	Keyhanasl et al. [195]

Table 8. Multi-objective designing issues of CHP energy systems.

Applied Algorithm	Energy System	Objective Functions	Authors/Ref.
NSGA- II	Micro-CHP gas turbine	Maximization of the exergy efficiency, minimization of the total production cost, and the CO_2 emission	Yazdi et al. [138]
GA	Diesel engine-based CHP	Maximization of the exergy efficiency, minimization of the total cost	Ganjehkaviri et al. [139]
GA	Hybrid solid oxide fuel cell and micro gas turbine CHP	Maximization of the exergy efficiency, minimization of the total cost	Sanaye et al. [140]
GA	High temperature proton exchange membrane fuel cell-based CHP	Minimization of the total cost, maximization of the net electrical efficiency	Haghighat-Mamaghani et al. [142]
NSGA-II	Wastewater treatment plant, integrated with a CHP plant	Minimization of the total cost and total environmental impacts	Lee et al. [144]
GA	CHP-HP	Maximization of the primary energy saving and annual expense saving, minimization of the CO_2 emission	Li et al. [145]
GA	Geothermal-fueled CHP plants	Maximization of the energetic and exergetic efficiencies, minimization of the total production cost	Ebadollahi et al. [146]
GA	Gas turbine-based CHP	Maximization of exergy efficiency, minimization of carbon emissions, minimization of payback period	Kazemiani-Najafabadi [151]
PSO	CHP, based on compressed air energy storage and humid air turbine	Maximization of the exergy and electrical efficiencies	Zhao et al. [165]
ICAB	Fuel cell-based CHP	Maximization of the electrical efficiency and the electrical power generation	Yang et al. [179]

Table 9. Multi-objective sizing issues of CHP energy systems.

Applied Algorithm	Energy System	Objective Functions	Authors/Ref.
GA	CHP-based microgrid	Minimization of the total cost, and carbon dioxide emission	Zidan et al. [156,157]
GA	PV-CHP plant, with hot water storage tank	Maximization of the system reliability, minimization of the energy cost	Assaf et al. [158]
NSGA-II	Petroleum gas and wet gas-fueled CHP	Minimization of the fuel cost, maximization of the gas turbine reliability, and pipeline integrity	Pujihatma et al. [159]
Sunflower Optimization	Fuel cell-based CHP	Minimization of the combined yearly maintenance and capital costs, maximization of the hydrogen energy consumption	Fan et al. [154]
PSO	CHP-based microgrid	Minimization of the power loss, the energy not-supplied, improvement of the voltage profile	Naderipour et al. [171]
SACSS	Fuel cell-based CHP	Minimization of the total cost, emissions, and voltage deviation	Niknam et al. [191]

Table 10. Economic emission dispatching issues of CHP energy systems (CHPEED optimization issues).

Authors	Applied Algorithm	Ref.
Basu	NSGA-II	[154]
Alomoush	SFS	[161]
Sun et al.	IDBEA	[163]
Jayakumar et al.	GWO	[173–175]
Shaabani et al.	Monte Carlo-TVAC-PSO	[183]
Dolatabadi et al.	WVO-PSO	[186]
Nourianfar et al.	TVAC-PSO-EMA	[187]
Sundaram	NSGA II-MOPSO	[188]
Sundaram	OBL-MMVO	[189]
Shi et al.	MLCA	[192]
Li et al.	θ-DEA	[193]

The statistical study of the presented multi-objective optimization issues, in four categories, shows the largest share of the CHPEED problem, among the other optimization matters. As it is shown in Figure 13, the CHPEED, other scheduling problems, designing, and sizing issues have 32%, 27%, 24%, and 17% of sharing, respectively. According to the obtained results, the CHPEED problems can be selected as the most useful multi-objective CHP optimization problem. Thus, in order to pay more attention to this significant issue, the numerical results of the CHPEED solved by different algorithms are presented and compared in Table 11. The results are based on a specified test system composed of four power-only units, two CHP units, and a heat-only unit. The considered constraints of each presented model are also mentioned in the table.

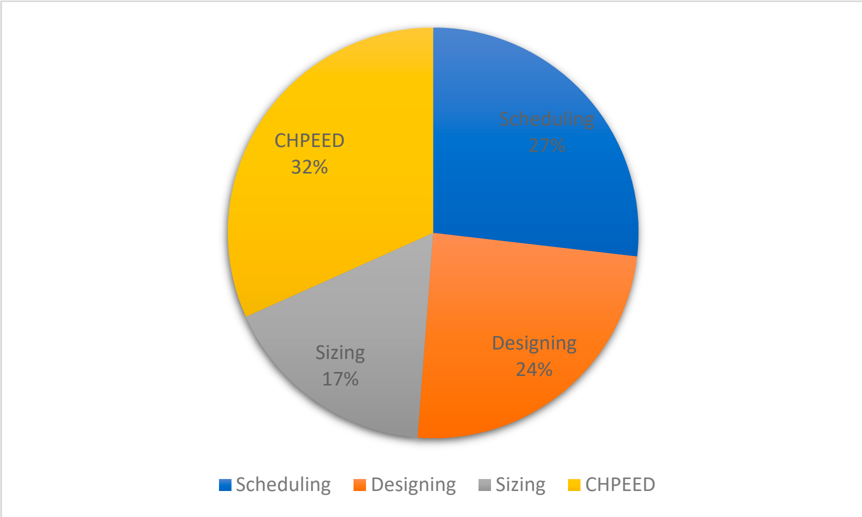

Figure 13. Sharing of the multi-objective CHP optimization issues per four categories.

Table 11. The numerical results of implementing different algorithms in a CHPEED optimization model *.

Applied Algorithm/Ref.	Total Cost (US$)	Total Emission (kg)	Computation Time (s)	Model Constraints
NSGA-II [154]	13,433.19	25.8262	9.7188	Heat and power demands, Capacity limits, Transmission loss
SFS [161]	10,111.06	21.5524	3.23	Heat and power demands, Capacity limits, Transmission loss
IDBEA [163]	12,957.2	17.3	2.0	Heat and power demands, Capacity limits, Valve point effect, Transmission loss
GWO [173]	10,111.0549	Not Mentioned	6.6	Heat and power demands, Capacity limits, Feasible operating regions of CHPs, prohibited operating zones of thermal generators
GWO [174]	12,402.90	17.4093	5.2618	Heat and power demands, Capacity limits, Valve-point effects, Transmission loss, Ramp-rate limits, Spinning reserve
GWO [175]	12,402.90	17.4093	5.2618	Heat and power demands, Capacity limits, Valve-point effects, Transmission loss, Ramp-rate limits, Spinning reserve
Monte Carlo method with TVAC-PSO [183]	10,244.0022	50.0453	NA	Heat and power demands, Capacity limits
WVO-PSO [186]	10,067.83	49.0832	NA	Heat and power demands, Capacity limits
NSGA II-MOPSO [188]	10,102	51.594	123.12	Heat and power demands, Capacity limits, Valve point effect, Transmission loss, Feasible operating region of the CHPs
MLCA [192]	12,451.38	11.1	NA	Heat and power demands, Capacity limits, Valve point effect, Transmission loss
θ-DEA [193]	13,282.9	9.7	NA	Heat and power demands, Capacity limits, Valve point effect, Transmission loss, Ramp rate limits

* The model consists of four power-only units, two CHP units, and a heat-only unit.

Based on Table 11, the reviewed algorithms applied to solve the CHPEED issues obtained a range of costs from 10,067.83 $ to 13,433.19 $. The lowest cost belongs to the WVO-PSO, while the highest cost has been obtained by the NSGA-II. It should be noted that the WVO-PSO algorithm did not perform well in terms of minimizing the emission level. A range of emission amounts has been obtained by different algorithms from 9.7 kg to 51.594 kg. The lowest emission level was obtained by the θ-DEA, and the highest emission level was achieved by the NSGA II-MOPSO. As it is evident from the results, the NSGA-II cannot be an ideal method for solving the CHPEED problems. The MLCA algorithm can be introduced, as one of the best methods for solving the CHPEED optimization problems. The best trade-off between the economic and environmental results was obtained by the MLCA; 12,451.38 $ and 11.1 kg as the total cost and total emission of the plant, respectively.

4. Concluding Remarks and Suggestions for Future Works

In this paper, a comprehensive review has been carried out, on various CHP optimization issues, solved by meta-heuristic algorithms. The main difference between this paper and previous related studies is the covering all types of CHP optimization problems including scheduling, designing, and sizing issues. This review study covers various CHP optimization models, such as the single-objective and multi-objective models. Different meta-heuristic routes have been discussed to solve the presented models and compared with each other in terms of the quality of the obtained solutions and the processing speed of the methods. According to a statistical analysis carried out in this paper, the CHPED and CHPEED optimization issues were selected as the most useful CHP optimization routes. In this paper, the application of different algorithms in various optimization problems was discussed. Based on these findings, the genetic algorithm, as the most useful evolutionary method is appropriate for solving single-objective CHP issues. Among the swarm intelligence-based methods, the PSO algorithm is appropriate for single-objective CHP issues. Additionally, it should be noted that the time-varying acceleration coefficients and self-adaptive mutation operators are the most efficient modifying strategies for the PSO algorithm in solving single-objective problems. On the other hand, to solve multi-objective CHP problems, the NSGA-II is the most useful evolutionary method. Another finding about the application of different algorithms in various optimization problems is the high application of the EAs in the multi-objective CHP design issues versus the high application of the PSO algorithms in the multi-objective CHP scheduling issues. Additionally, the hybrid mathematical-metaheuristic methods are known as the great solvers for stochastic CHP optimization models; the PEM and Monte Carlo methods are the most efficient mathematical methods. The PFCOA and The EDHS algorithms. The significant conclusions of this study are as follows:

- In the single-objective problems, the CHPED issue as a subcategory of the scheduling problems is introduced as the most paid topic.
- In the single-objective problems, the designing issue is known as the lowest paid topic.
- In the multi-objective problems, working on various types of CHP optimization problems has been conducted with an almost similar share. The CHPEED problem with the most share, and the sizing issue with the lowest share.
- Introducing the CHPEED problem, as one of the most useful multi-objective CHP optimization models.

Based on the studies, the research gaps in CHP optimization are the designing and sizing optimization problems. Working more on these topics could be suggested for future works.

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Abbreviations

CHP	Combined Heat and Power	SSA	Squirrel Search Algorithm
DG	Distributed Generation	GWO	Grey Wolf Optimization
EMPC	Economic Model Predictive Control	HSA	Harmony Search Algorithm
CHPED	Combined Heat and Power Economic Dispatch	TLBO	Teaching Learning-based Optimization
CHPEED	Combined Heat and Power Economic Emission Dispatch	EMA	Exchange Market Algorithm
EAs	Evolutionary Algorithms	SCO	Social Cognitive Optimization
SI-based algorithms	Swarm Intelligence-based algorithms	ED	Economic Dispatch
GAs	Genetic Algorithms	EDHS	Economic Dispatch Harmony Search
SQP	Sequential Quadratic Programming	IHS	Improved Harmony Search
PS	Pattern Search	MPHS	Multi-Player Harmony Search
MR	Maximum Rectangle	TSCO	Tent Map Social Cognitive Optimization
SARGA	Self-adaptive Real-coded Genetic Algorithm	CSSA	Charged System Search Algorithm
RCGA	Real Coded Genetic Algorithm	GSA	Gravitational Search Algorithm
RCGA-IMM	Real Coded Genetic Algorithm with Improved Mühlenbein Mutation	HTS	Heat Transfer Search
IGA-NCM	Improved Genetic Algorithm using Novel Crossover and Mutation	SALCSSA	Self-Adaptive Learning Charged System Search Algorithm
MG	Microgrid	SA	Simulated Annealing
NSGA- II	Non-dominated Sorting Genetic Algorithm II	PV	Photovoltaic
DE	Differential Evolution	TVAC-GSA-PSO	Time Varying Acceleration Coefficients-Gravitational Search Algorithm- Particle Swarm Optimization
EP	Evolutionary Programming	CSA-BA-ABC	Chaotic based Self Adaptive-Bat Algorithm-Artificial Bee Colony
PSO	Particle Swarm Optimization	E-PSO	Evolutionary Particle Swarm Optimization
DER	Distributed Energy Resources	BBO	Biogeography-based Optimization
SADE	Self-Adaptive Differential Evolution	SABBO	Simulated Annealing with Biogeography-based Optimization
DEGM	Differential Evolution with Gaussian Mutation	BMO	Bird Mating Optimization
IDE	Improved Differential Evolution	OBL	Opposition-based Learning
AIS	Artificial Immune System	OGSO	Opposition-based Group Search Optimization
HSS	Hyper-Spherical Search	PEM	Point Estimate Method
SFS	Stochastic Fractal Search	DED	Dynamic Economic Dispatch
SPSO	Selective PSO	MILP	Mixed Integer Linear Programing
TVAC-PSO	Time-Varying Acceleration Coefficients Particle Swarm Optimization	TOC	Total Operating Cost
MPSO	Modified Particle Swarm Optimization	TAC	Total Annual Cost
MTPSO	Multi-Team Particle Swarm Optimization	CSO	Civilized Swarm Optimization
ESS	Energy Storage System	PPS	Powell's Pattern Search
AMPSO	Advanced Modified Particle Swarm Optimization	TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
SRPSO	Self-Regulation Particle Swarm Optimization	CHP-HP	Combined Heat and Power and Heat Pump
CSA	Cuckoo Search Algorithm	EELD	Economic Emission Load Dispatch
ECSA	Effective Cuckoo Search Algorithm	IDBEA	Indicator and crowding Distance-based Evolutionary Algorithm
PFCOA	Penalty Function Cuckoo Optimization Algorithm	PL	Priority List
WOA	Whale Optimization Algorithm	DRP	Demand Response Program
IWOA	Improved Whale Optimization Algorithm	MOBCC	Multi-Objective Bacterial Colony Chemotaxis
GSO	Group Search Optimization	ICAB	Improved Collective Animal Behavior
MGSO	Modified Group Search Optimization	SBSO	Self-adaptive Bee Swarm Optimization
BCO	Bee Colony Optimization	MCSA-DE	Modified Cuckoo Search Algorithm and Differential Evolution
ABC	Artificial Bee Colony	WVO	Weighted Vertices-based Optimizer
IABC	Improved Artificial Bee Colony	MOPOS	Multi-Objective Particle Swarm Optimization
FA	Firefly Algorithm	MMVO	Multi-objective Multi-Verse Optimization
MFA	Modified Firefly Algorithm	SACSS	Self-Adaptive Charged System Search
ACSA	Ant Colony Search Algorithm	MLCA	Multi-objective Line-up Competition Algorithm
		θ-DEA	θ-Dominance based Evolutionary Algorithm

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