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Review

Review: Multi-objective optimization methods and application in energy saving

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ABSTRACT

Multi-objective optimization problems are difficult to solve in that the optimized objectives are usually conflicting with each other. It is usually hard to find an optimal solution that satisfies all objectives from the mathematical point of view. Unlike analytical methods and classical numerical methods, which require strict mathematical calculation or defined initial search values, intelligent optimization algorithms are heuristic algorithms able to find global optimal solutions. In this paper, we make a brief introduction of multi-objective optimization problems and some state-of-the-art intelligent algorithms. In order to get the final optimal solution in the real-world multi-objective optimization problems, trade-off methods including a priori methods, interactive methods, Pareto-dominated methods and new dominance methods are utilized. Moreover, we give a review of multi-objective optimization methods application in the environmental protection fields, for optimization objectives of energy saving, emissions reduction and cost reduction, etc. At last, a whole summary about current difficulties existed in the multi-objective optimization problem is given out, serving as suggestions or guidance for future researches.

Contents

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1. Introduction

In the world today, people are paying more and more attention to cost minimization, output maximization, energy saving, environmental protection, and sustainable development issues, etc. in various fields. Therefore, us human beings should manage our production, manufacturing, experiments, and living activities in a more efficient and friendly way. Furthermore, these improvement problems in the scientific research and engineering fields boil down to optimization problems of materials, products, resources and energy utilization. However, along with the competitive development of technologies and economies around the world, optimization problems become more complicated with larger scale, more highly nonlinearity, more objects and constraints.

Optimal problems can be continuous or combinatorial (with continuous or discrete decision variables) optimization problems, constrained or unconstrained optimization problems, linear or nonlinear optimization problems, static or dynamic (off-line or online) optimization problems, single objective or multi-objective optimization problems [1]. To solve optimization problems, we usually take two steps: firstly, we model the optimization problem and transfer it into regular expressions, thus to define the decision space, object space and the mapping relation between them; then we use appropriate and efficient methods to solve those regular expressions to get the optimal solution or solutions.

Most of the real-world problems, including design, optimization, scheduling and control etc. are inherently characterized by multiple conflicting objectives realization. When addressing these problems, the parameters or variables are frequently imprecise due to uncontrollable factors, leading to more complicated problem formulation. Unlike single objective optimization, the most difficulty in solving multi-objective optimization problems lies in that there does not exist a mathematical explainable solution because of the highly complex nature of simultaneously satisfying several objectives, which are usually conflicting to each other. Thus, it is necessary to determine a set of points that represent the optimal solutions and form the Pareto frontier [2]. All points along the frontier are mathematically equal and valid, and resulting in different values for each objective. Although the achieved solutions are of no preference, from a practical viewpoint, decision makers usually need only one final solution on the basis of their own preferences for the conflicting and incommensurable objectives [3,4].

Besides, countries around the world have already started to focus on issues of energy saving and emissions reduction, which is an important way to reach the economic and environmental objectives. As classical energy resources like coal, oil, natural gas, etc. have decreased in amount and renewable resources like wind, solar energy, recyclable water, etc. are under development, how to improve energy efficiency and effectively utilize limited energy becomes an important consideration in industrial processes and daily lives. On the other hand, production and living activities of human beings have already posed big influences on the earth, especially bad influences. For the sustainable development of earth as well as all beings on the earth, environmental protection has been and will be of great importance. Consequently, realizing energy saving and emissions reduction of industrial and living activities is beneficial for sustainable development.

Therefore, in this paper, we give an overall systematic overview about multi-objective optimization methods and application in energy saving. The paper is organized as follows: Section 2 makes the general definition of the multi-objective optimization problems and solutions. Section 3 describes in general developments of optimization algorithms, which are able to solve multi-objective optimization problems and produce the optimal solutions as a set. In the following, Section 3 lists theoretical test functions for evaluating the performance of multi-objective optimization algorithms. Section 4 introduces common trade-off methods for achieving the final trade-off solution based on preferences of decision makers or historical experiences. Besides, the brief applications of multi-objective optimization methods in various energy-consuming industrial processes, for optimization objectives of energy saving and emissions reduction are presented in Section 5. Furthermore, Section 6 gives the summary of current difficulties and future directions for research on multi-objective optimization methods and application in energy saving, while Section 7 makes the whole conclusion.

2. Multi-objective optimization problems

2.1. Multi-objective optimization problems

Optimization problems are one of the most common and primary problems in both scientific research and engineering practice. According to the number of optimized objective function, optimization problems can be classified into two categories: single objective optimization problem and multi-objective optimization problem. For multi-objective optimization problems (MOPs), two or more objective functions need to be calculated simultaneously. Moreover, these objective functions are always contradictory to each other. A solution good for one function may be bad for another function or other functions. Therefore, it is hard for a multi-objective problem to search for a solution that satisfies all objective functions. In this situation, there exists a set of feasible solutions.

The expressions for describing different kind of optimization objectives may be different, either be maximum functions or be minimum functions. These two extremum functions can be transferred to each other through the following equation [2].

$$\max\{f(\boldsymbol{x})\}\Leftrightarrow\min\{-f(\boldsymbol{x})\} \tag{1}$$

Therefore, any multi-objective optimization problem can be expressed as the following common mathematical model:

$$\min \boldsymbol{y}=f(\boldsymbol{x})=[f_1(\boldsymbol{x}),f_2(\boldsymbol{x}),\ldots,f_m(\boldsymbol{x})]^T \tag{2}$$

$$\begin{array}{l} \text{s.t } g_i(\boldsymbol{x})\le 0(j=1,2,\ldots,p) \\ h_k(\boldsymbol{x})=0(k=1,2,\ldots,q) \\ x_i^{\min}\le x_i\le x_i^{max}(i=1,2,\ldots,n) \\ \mathbf{x}=[x_1,x_2,\ldots,x_n]^T\in\Theta \\ \mathbf{y}=[y_1,y_2,\ldots,y_m]^T\in\psi \end{array} \tag{3}$$

where in, m is the number of optimized objective functions, $\Theta$is a n-dimensional search space and is determined by the upper bound $\mathbf{x}^{\max}=[\mathrm{x}_1^{\max},\mathrm{x}_2^{\max},\ldots,\mathrm{x}_n^{\max}]^{\mathrm{T}}$ and the lower bound $\mathbf{x}^{\min}=[\mathrm{x}_1^{\min},\mathrm{x}_2^{\min},\ldots,\mathrm{x}_n^{\min}]^{\mathrm{T}}$ of decision variables $\mathrm{x_i}(\mathrm{i}=1,2,\ldots,\mathrm{n})$. $\Psi$is the m-dimensional vector space of objective functions and is determined by$\Theta$and the objective function $f(\boldsymbol{x})$. Equations $g_j(\boldsymbol{x})\le 0(j=1,2,\ldots,p)$ and $\mathrm{h_k}(\mathbf{x})\le 0(\mathrm{k}=1,2,\ldots,\mathrm{q})$ denote p inequality constraints and q equality constraints. Especially, if $p=q=0$, then the problem is simplified as an unconstrained multi-objective optimization problem.

2.2. Multi-objective optimization solutions

In multi-objective optimization problems, a primary issue is how to define the solutions. From the viewpoint of theoretical mathematics, there is not one single solution for multi-objective problems, but there are a set of solutions. In 1951, Koopmans [5] first put forward the concept of Pareto efficient solution set, which effectively described the solution under the relationship of the partial order but not the total order.

Definition 2.1, feasible solution: For a solution vector $\mathbf{x}\in\Theta$, if it satisfies both inequality constraints and equality constraints for all $j=1,2,\ldots,p$ and $\mathrm{k}=1,2,\ldots,q$, it is defined as a feasible solution, else it is a infeasible solution.

All feasible solutions construct a set named feasible domain Ω. All infeasible solutions construct the set named infeasible domain $\overline{\Omega}$. Apparently, $\overline{\Omega}+\Omega=\Theta$, where $\Omega\subseteq\Theta$ and $\overline{\Omega}\subseteq\Theta$.

Definition 2.2, decision variable domination: For two vectors in the decision variable space $\boldsymbol{a}=[a_1,a_2,\ldots,a_n]^T$ and $\boldsymbol{b}=[b_1, b_2,\ldots,b_n]^T$, if $\forall i\in\{1,2,\ldots,m\}, f_i(\boldsymbol{a})\le f_i(\boldsymbol{b}), and\ \exists\ j\in\{1,2,\ldots,m\}, f_j(\boldsymbol{a})<f_j(\boldsymbol{b})$, then we say that b is dominated by a, expressed as $\mathrm{b}\prec\mathrm{a}$.

Definition 2.3, objective function domination: For two vectors in the objective function space $\mathbf{g}=[\mathrm{g}_1,\mathrm{g}_2,\ldots,\mathrm{g}_\mathrm{m}]^{\mathrm{T}}$ and $\boldsymbol{h}=[h_1, h_2,\ldots,h_m]^T$, if $\forall i\in\{1,2,\ldots,m\}, \boldsymbol{g}_i\le\boldsymbol{h}_i, and\ \exists\ j\in\{1,2,\ldots,m\}, \boldsymbol{g}_j<\boldsymbol{h}_j$, then we say that h is dominated by g, expressed as $\mathrm{h}\prec\mathrm{g}$.

Definition 2.4, Pareto optimal solution: If the vector $\mathbf{x}=\{\mathrm{x}_1^*,\mathrm{x}_2^*,\ldots,\mathrm{x}_\mathrm{n}^*\}$ satisfies the condition $\neg\exists\mathbf{x}\in\Theta,\mathbf{x}\succ\mathbf{x}^*$, then $\mathbf{x}^*$ is called a global Pareto optimal solution, or optimal solution for short. All global Pareto optimal solutions constitute a global Pareto optimal set, expressed as PS^*.

Definition 2.5, Pareto optimal front: The Pareto optimal set presented in the objective function space is called Pareto optimal front, which is expressed in the following way:

$$\mathrm{P}F^*=\{f(\boldsymbol{x}^*)\,|\,\boldsymbol{x}^*\in PS^*\}$$

Definition 2.6, non-dominated solution: In the computation process of evolutionary algorithms, the optimal solution in each generation of evolution population is called non-dominated solution. All non-dominated solutions constitute non-dominated solutions (abbreviated as NDS). Multi-objective optimization aims at searching for such non-dominated solutions to approximate real optimal solutions.

As shown in Fig. 1., the relationship between the design space and the objective space was demonstrated, as well as the Pareto optimal solutions definition. In the left graph was the simplified decision space, while the right graph was the objective function space. Certain mapping relations were established between these two spaces. The infeasible regions drawn in both spaces were regions out of feasible solutions, which were determined by constrains of the optimization problems. The six points listed in the decision space was mapped into the objective function space and the dominance relations were presented as: A≻D, A≻C, D≻C, B≻F, B≻C. The point E was an infeasible solution. A and B points were non-dominated solutions in the Pareto front, and there were dominance relations neither between A and B, nor between D and F points.

Multi-objective optimization methods try to get solutions that are as close as possible to the Pareto optimal front and are also uniformly distributed. Such methods will have good convergence and diversity. After the Pareto optimal set is found, decision makers need to select from these optimal solutions the final solution according to concrete optimization problems or personal preferences.

3. Multi-objective optimization algorithms and performance test functions

3.1. Multi-objective optimization algorithms

Up till now, there are mainly two kinds of methods to solve optimization problems [1]: analytical method and numerical method. The analytical method involves strict mathematical proofs and derivation, and it can reach exact solution. However, the method is also strict with the problem characteristics, which many realistic problems could not match. The numerical method is designed with appropriate iteration formulas and applied with a series of iterations to get the approximate solution. It needs only defined decision variables and objective variables feedback from optimization problems. The optimization problem can be a black-box problem without obvious expressions and it is more suitable for realistic problems.

Among the numerical methods [6], classical methods like Newton iteration method, simplex method, conjugate direction method, etc. are oriented at single objective optimization problems. These methods have high searching efficiency and fast convergence speed, because they usually start with a given initial point and calculate the next iteration point according to the descending information such as gradient. However, the methods have difficulties in solving problems whose gradient information cannot or need too much to be calculated. When applied for solving multimodal objective functions, classical numerical methods are easy to fall into and hard to escape from local optimum solutions. Moreover, the

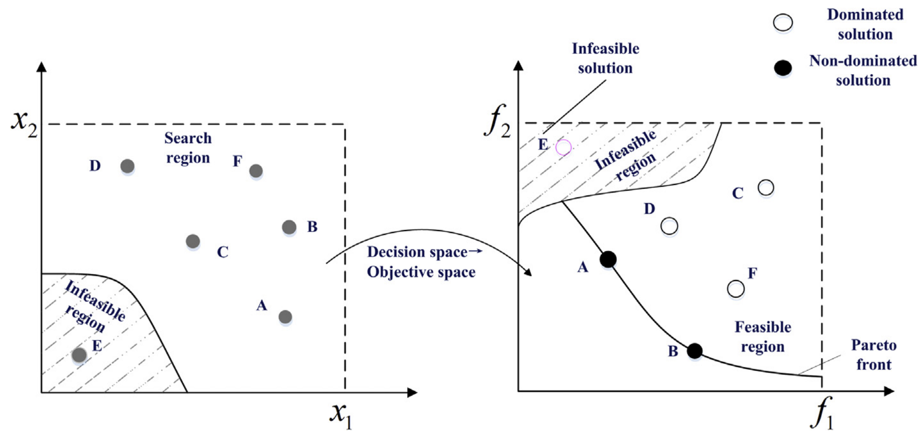

Fig. 1. Relationship between the design space and the objective space and solution definition of a two-objective problem.

methods find only one single solution in each iteration step, and the accuracy of the solution depends mostly on the setting of initial values.

Intelligent numerical methods, as one sort of heuristic search algorithm, are inspired by behaviors, reactions and communication mechanisms in nature. Thus developed optimization algorithms are broadly divided into four categories [7] as shown in Fig. 2: Biology inspired algorithms, Physics inspired algorithms, Geography inspired algorithms, and Social culture inspired algorithms.

3.1.1. Biology inspired algorithms

Biology inspired algorithms are inspired from biological activities in both micro and macro world (such as evolution behaviors), or from substantial development and structural features [8]. They are generally divided into two types: evolution based algorithms and swarm based algorithms [9].

3.1.1.1. Evolution based algorithms. Evolution based algorithms, also known as Evolutionary Algorithms (EA) are stochastic search methods that mimic the survival of the fittest process of natural ecosystems. The algorithms have strong adaptability and self-organization, including Evolutionary Programming (EP) [10], Evolutionary Strategy (ES) [11], Genetic Algorithm (GA), Differential Evolution Algorithm (DE), Harmony Search Algorithm (HS), Membrane Computing (P system), etc. [12].

The development process of classical genetic algorithms and differential evolution algorithms are respectively demonstrated in Tables 1 and 2.

Moreover, Jia et al. [31] added chaos neighborhood searching mechanism to DE to improve its search ability in the early search stage and exploration ability in the later search stage. Liu et al. [32] combined DE with PSO to form a hybrid algorithm, which improved the performance and accelerated the searching efficiency. The hybrid algorithm worked especially well for solving constrained optimization problems.

Membrane computing [33], also known as a P system, is non-deterministic and distributed parallel computing device, which is abstracted from the structure and functioning of living cells, as well as from the interactions of living cells in tissues or neuros. It was initiated by Păun in 1998, with the first paper published in 2000 [34]. The structure is consisted of several cell-like membranes, placed inside a solo skin membrane. Multisets of objects are placed in the regions delimited by hierarchical or more general arrangements of membranes, as shown in Fig. 3. The evolution processes of each object are done in a parallel manner. At last, the evolved result is output from the skin membrane to the environment. There are mainly three types of P systems: cell-like P systems; tissue-like P systems and neural-like P systems [35].

It has been proved that any Turing computable problems can be solved by P systems. The P system has already applications in

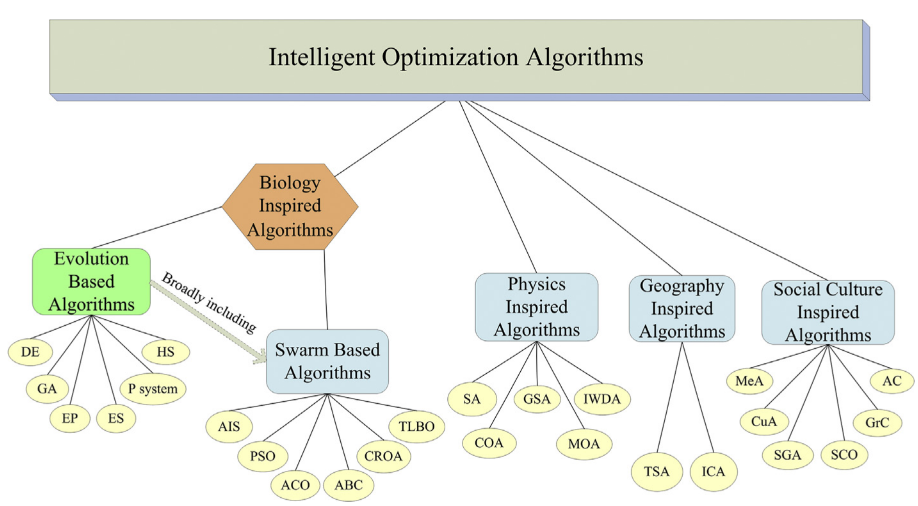

Fig. 2. Classification of intelligent optimization algorithms.

Table 1
Important developments of genetic algorithms.

Genetic algorithms developments	Initially proposed time	Proposers	Run-time complexity [2,26]
GA	1975	Holland [13]	
VEGA (vector-evaluated genetic algorithm)	1985	Schaffer [14]	
MOGA (Multiobjective Genetic Algorithm)	1993	Fonseca and Fleming [15]	$O(GmN^2)$
NSGA (Non-dominated Sorting Genetic Algorithm)	1993	Srinivas and Deb [16]	$O(GmN^2)$
NPGA (Niched Pareto Genetic Algorithm)	1994	Horn and Nafpliotis [17]	$O(GmN^2)$
SPEA (Strength Pareto Evolutionary Algorithm)	1999	Zitzler and Thiele [18]	$O(Gm(N+A)^2)$
PAES (Pareto Archived Evolution Strategy)	2000	Knowles and Corne [20]	$O(GN \log^{M-1}A \log \log A)$
PESA (Pareto Envelope-Based Selection Algorithm)	2000	Corne, Knowles and Oates [21]	$O(GN \log^{M-1}A \log \log A)$
PESA-II	2001	Knowles, Jerram, Corne, et al. [22]	$O(GmNA)$
NPGA2	2001	Erichson et al. [23]	
Micro-GA	2001	Coello Coello et al. [24]	
SPEA2	2002	Zitzler, Laumanns and Thiele [19]	$O(Gm(N+A)^2)$
NSGA-II	2002	Deb et al. [25]	$O(GN \log^{M-1}N)$

Table 2
Variants of differential evolution algorithms.

Differential evolution algorithms	Initially proposed time	Proposer
DE	1995	Storn and Price [27]
FADE (adaptive differential evolution algorithm based on fuzzy theory)	2005	Liu and Lampinen [28]
SaDE (scaling factor adaptive adjustment differential evolution)	2009	Qin et al. [29]
MOSaDE (multi-objective SaDE)	2009	Huang [30]

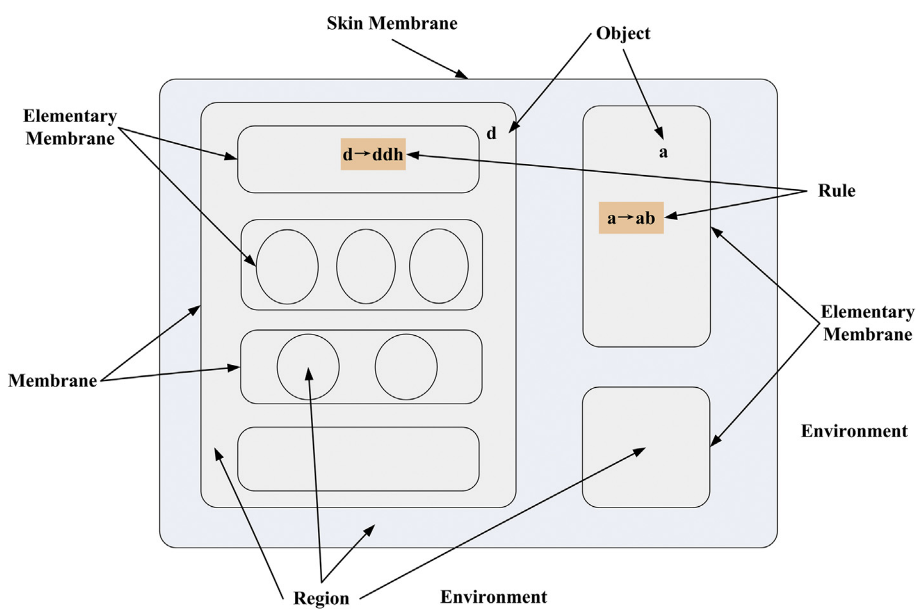

Fig. 3. A membrane structure.

computer graphics, computer science, cryptography, mathematics, abstract chemistry, biology, ecology, artificial intelligence, approximate optimization, and even linguistics, etc. [36–42].

HS was originally developed by Geem [43] for discrete-variable problems and then expanded to continuous-variable problems. It mimics musician's behaviors such as random play, memory-based play and pitch adjusted play to get a perfect state of harmony. Wang et al. [44] proposed a differential harmony search (DHS) algorithm, combining the mechanisms of differential evolution with harmony search. The DHS enhances the exploration ability of the algorithm.

3.1.1.2. Swarm based algorithms. In a broadly defined way, swarm based algorithms are included in evolution based algorithms. Swarm based algorithms are inspired from social nature and model the collective behavior of populations, such as honey bees, ant colonies, and bird flocks, etc. Among these agents (swarm individuals), they cooperate with each other to search for food, necessary for their survival, and also keep safe from other agents. Swarm based algorithms are consisted of Particle Swarm Optimization Algorithm (PSO), Artificial Bee Colony Algorithm (ABC) [45], Artificial Immune System (AIS), Teaching-Learning Based Optimization algorithm (TLBO), Ant Colony Optimization Algorithm (ACO) [46], Cuckoo Search algorithm (CS) [47], Firefly Algorithm (FA) [48], Bacteria Foraging Optimization algorithm (BFO) [49], Coral Reef Optimization algorithm (CROA) [50], Shuffled Frog Leaping Algorithm (SFLA) [51], Pigeon Inspired Optimization (PIO) [52], etc.

In 1987, Christopher initially proposed the concept of Artificial

Life, which meant the system that mimic the behavior characteristics in the nature life system, by the way of computers or other non-biological media [53,54]. The above mentioned evolution-based algorithms are inspired by Darwinian evolution whereas the swarm intelligence is generated by imitating the behaviors of social swarms [55]. Swarm intelligence [56] meant the intelligent behaviors presented by simple behaviors of individuals in the population without central control. These individuals behaved to solve the foraging, searching and visiting, transportation and transmission problems. Based on the swarm intelligence, swarm-based algorithms were then produced.

3.1.1.2.1. Particle swarm optimization (PSO). In 1995, Kennedy and Eberhart [57,58] proposed the PSO algorithm, whose central idea was information sharing mechanism. The PSO has been widely used in various fields to solve different kinds of optimization problems. Many variants of the PSO algorithm have been proposed to maintain or strengthen the diversity, so as to escape from local optima or premature convergence. Li et al. [59] combined PSO with NSGA-II and the experiment results showed that the combined method had better performance than NSGA-II. Coello Coello et al. [60] proposed the multi-objective PSO (MOPSO), which incorporated external population with adaptive grids.

3.1.1.2.2. Teaching-learning based optimization (TLBO). The TLBO algorithm was first proposed by Rao et al. [61]. There are two phases in the TLBO: teacher phase and learner phase. Learners learn from the teacher in the teacher phase and from each other in the learner phase. The teacher is considered as the best solution in the entire population obtained thus far. In order to get the global optimal solutions, a modified TLBO algorithm was proposed by Hosseinpour et al. [62], which added a mutation process similar to that of DE. Niknam et al. [63] proposed a modified TLBO algorithm with two mutation operations and two crossover operations added, so as to enhance the local and global search abilities of the algorithm. TLBO also shows good performance in solving large scale optimization problems with little computational efforts [64].

3.1.1.2.3. Artificial Immune System (AIS). The AIS is inspired from immunology and acts as an adaptive system that mimics the function, principles and model of immunology to solve complicated problems [65]. It has been successfully applied in fields of anomaly detection, computer security, data mining, optimization, etc. In Table 3 illustrated are developments of AIS. Wherein, the NNIA is especially advantageous in solving many-objective optimization problems with more than three optimization objectives.

Compared to classical numerical methods, broadly defined evolution based algorithms is one sort of probability search algorithm based on population. These algorithms need neither extra initial points nor gradient information of objective functions. Therefore, they are suitable for optimization problems that cannot be solved by classical numerical methods. Moreover, evolution based algorithms have characteristics of parallelism and distribution, appropriate for solving large-scale/high-dimensional optimization problems.

3.1.2. Physics inspired algorithms

Physics inspired algorithms for optimization problems are also heuristic algorithms. They imitate the physical behaviors and properties of the matters or follow the same philosophy as the laws of physics. The common physics inspired algorithms include Chaotic Optimization Algorithm (COA), Intelligent Water Drops Algorithm (IWD) [68], Magnetic Optimization Algorithm (MOA) [69], Gravitational Search Algorithm (GSA) [70,71], Simulated Annealing (SA) [72,73], etc.

3.1.2.1. Chaotic Optimization Algorithm (COA). The random search technique was introduced by Hamzacebi and Kutay [74], which was adaptable to different optimization problems and the simplest heuristic algorithms. As introduced by Vela'squez Henao [75], the use of chaotic sequences instead of quasi-random numbers seemed to be a more powerful strategy for improving many traditional heuristic algorithms, because the chaotic sequences have characteristics of ergodicity, randomness, and regularity. An essential feature of chaotic systems is that small changes in the parameters or the initial values lead to vastly different future behaviors [76].

The chaos optimization algorithm (COA) was first proposed in 1997 by Li et al. [77], in which the Logistic map was introduced to produce chaos variables as optimization variables. Besides Logistic map, other mapping methods were also incorporated in the COA, such as Tent map [78,79]. The COA was also combined with other algorithms to form hybrid chaos optimization methods [80–82].

3.1.3. Geography inspired algorithms

Geography inspired algorithms are one sort of metaheuristic algorithm and generate random solutions in the geographical search space. These optimization algorithms are classified as Tabu Search Algorithm (TS), Imperialistic Competition Algorithm (ICA), etc.

3.1.3.1. Imperialistic Competition Algorithm (ICA). The ICA is inspired by imperialism, which is the policy of extending power and signifies the role of a government [83]. The number of colonies determines the power of an imperialist. Strengthening the authority of an imperialist makes other imperialists weaker.

3.1.3.2. Tabu Search Algorithm (TS). Tabu search algorithm was first suggested by Glover [84] in 1986, which was a meta-heuristic search method based on local search. It explores all feasible solutions in the search space by a sequence of moves. Especially, a set of moves are forbidden at each iteration step to escape from local minima [85].

3.1.4. Social culture inspired algorithms

Social culture inspired algorithms are inspired by the social, economic and cultural systems etc. that incorporate the cultural evolution theory into optimization algorithms.

As shown in Table 4, there are some classical developments of social culture inspired algorithms.

In 1989, Moscato firstly proposed the Memetic Algorithm, which used the local heuristic search to imitate the mutation process backed up by large amount of professional knowledge. The Granular Computing mimics the human thoughts from different levels of granules. It is based on the space partition of problem concepts, able to effectively analyze and deal with problems of fuzziness, non-accuracy, non-consistency and partial true values.

In summary, Fig. 4 demonstrates the overall development

Table 3
Developments of the artificial immune system.

Developments of the artificial immune system	Initially proposed time	Proposer
AIS	1998	Dasgupta [65]
MISA (multi-objective immune system algorithm)	2005	Coello Coello et al. [66]
NNIA (non-dominated neighborhood immune algorithm)	2008	Gong et al. [67]

Table 4
Developments of social culture inspired algorithms.

Social culture inspired algorithms	Source of inspiration	Initially proposed time	Proposer
MeA (Memetic Algorithm)	Social culture	1989	Moscato [86]
CuA (Cultural Algorithm)	Social culture (signal, knowledge, etc.)	1994	Reynolds [87]
SCO (Social Cognitive Theory)	Social cognitive process	2002	Xie [88]
SGA (Selfish Gene Algorithm)	Selfish gene in human beings	1998	Corno et al. [89]
GrC (Granular Computing)	Information cognition	1996	Lin [90]
AC (Affective Computing)	Social and cultural affection, etc.	1997	Picard [91]

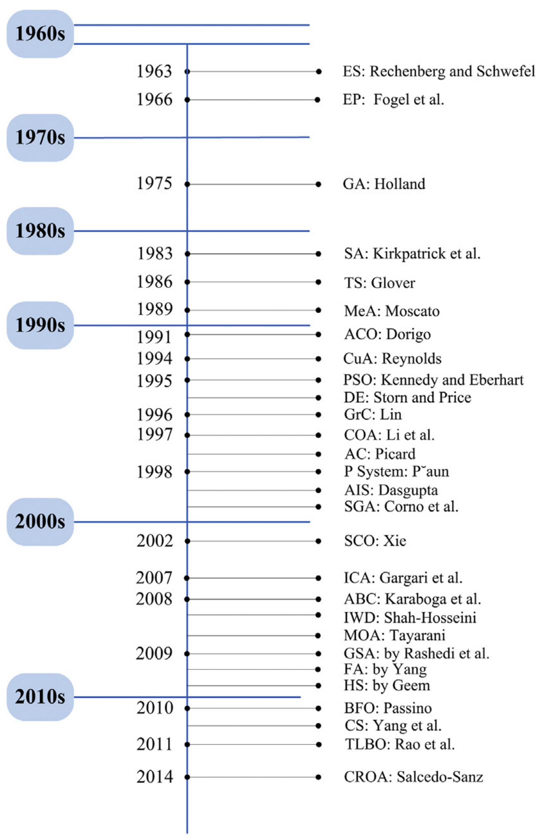

Fig. 4. Development process of common intelligent optimization algorithms.

process of common intelligent optimization algorithms. At the same time, description of advantages and disadvantages of some classical intelligent optimization algorithms are listed in Table 5.

Zhou et al. [92] surveyed the development of MOEAs (multi-objective EAs) in detail. In the paper covered included algorithmic frameworks and applications such as MOEAs with specific search methods, MOEAs for multimodal problems, constraint handling in or with MOEAs, computationally expensive multi-objective optimization problems (MOPs), dynamic MOPs, combinatorial and discrete MOPs, and etc. There was also a summary of the major applications of MOEAs in solving real-world problems.

Rodrigues et al. [93], Cambero et al. [94], Chaouachi [95], H.A. et al. [96], and Fadaee et al. [97] reviewed the application of intelligent algorithms (especially EAs) in the multi-objective optimization of economic, energy, environment, or technical issues in the fields of wind farm, forest biomass supply chains, micro-grid, distribution generation systems, and hybrid renewable energy systems. They found out that intelligent algorithms were utilized effectively able to find global optima.

The PSO algorithm was one of the most popular intelligent algorithms that were applied for solving multi-objective optimization problems considering energy, economics and environment issues in processes that produced or consumed energy [7]. As renewable energy resources are clean and environment-friendly, they are paid enormous attention in recent years. PSO [98] or its improved variants like MOPSO [99], AMOPSO [100], BB-MOPSO [101], and LAPSO [102] etc. were tested efficient in energy optimization applications.

Meanwhile, GA, with most accepted and applied variants (including VEGA, MOGA, SPEA, SPEA2, NSGA, NSGA-II, PESA, PESA-II, NPGA, NPGA2, etc.) were also used or improved varying with concrete multi-objective optimization problems, like building energy optimization [103,104], distribution transformer optimal design [105], complex industrial processes [106–108], or processes integrated renewable resources [109].

New methods are proposed every day to solve multi-objective optimization problems. Besides, combined methods based on the classical optimization method and the intelligent optimization algorithm or on two kinds of intelligent algorithms are being developed for various real-world multi-objective optimization problems. Intelligent algorithms applications in energy and environment protection optimization issues will be discussed in detail in Section 5.

3.2. Multi-objective optimization test functions and performance evaluation indexes

3.2.1. Multi-objective optimization test functions

As it is hard to evaluate the performance parameters of intelligent algorithms theoretically, researchers generally use test functions to verify the algorithm performances. Zitzler et al. [110] constructed a set of test problems called ZDT test function set, which was consisted of six problems ZDT1~ZDT6. These problems are two-objective optimization problems with different forms of expression and properties. Because their Pareto fronts are known, they are one of the most common used test problems. Therein, ZDT1 and ZDT4 are convex functions while ZDT2 and ZDT6 are concave functions, ZDT3 is a non-continuous function, ZDT4 is a multi-modal function, and ZDT5 is a function with deceptive property.

Deb et al. [111] constructed a set called DTLZ test function set, which allowed the decision variables and objective functions to extend to any dimension. The DTLZ test function set includes seven unconstrained optimization problems DTLZ1~DTLZ7 and two constrained optimization problems DTLZ8~DTLZ9. They are also widely used for testing the performance of optimization algorithms. Deb et al. [112] also constructed a set of constrained multi-objective optimization problems (called DEB) with different Pareto optimal boundaries. Huband et al. [113] defined a set of WFG test problems, and constructed a scalable toolkit of test problems. Li and Zhang [114] proposed a set of continuous test problems whose variables were correlative and the Pareto front surface was with arbitrary complexity, which was able to reflect the complexity in the real-world multi-objective optimization problems. There are also some other common test problems like Schaffer's study (SCH) [115], Fonseca and Fleming's study (FON) [116], Kursawe's study (KUR) [117], etc.

Table 5
(Dis)advantages of some classical intelligent optimization algorithms.

Intelligent optimization algorithms	Advantages	Disadvantages
GA(NSGA-II)	Good diversity of solutions (using the environment selection strategy based on neighborhood rules (in SPEA2), or the elitist keeping mechanism); Uniform distribution of Pareto solutions with good performance (based on the crowding distance method); Relatively low computation complexity (fast non-dominated solution ranking method).	Premature or long time convergence; Probable loss of best solutions; Not guaranteed to find a global optimum.
DE	Easy to understand and strong robustness; Few parameters need to be adjusted; Able to tackle non-differentiable, non-linear and multimodal functions promptly.	Its parameters need to be preset; Parameters have important influences on the algorithm performance.
P System	Understandable, scalable and programmable; Parallel execution manner; Adequate for handling discrete processes.	A relatively new and developing method, not mature in application.
HS	Only a few parameters and easy to be implemented.	Slow convergence speed and weak search guidance.
PSO	Simple procedures and not complex adjustment; Easy to be implemented with relatively fast speed; Able to escape from the local optima and find the global optimal solutions in most cases.	Not sure to be strictly convergent; Relatively weak local search ability; Probable to be immersed in local optima in multi-modal problems.
TLBO	Good learning abilities and parameter-free. Good performance in solving large scale optimization problems with little computational efforts.	Relatively low local search ability; Premature convergence due to lack of sufficient information sharing; Easy to be immersed in local optima when dealing with low dimension and complicated solution space.
AIS	Distributed, self-organizing and self-adaptable structure; Parallel and robust in execution; High search efficiency; Able to escape from premature convergence; Suitable for dealing with problems with constraints and multiple criteria.	Not profound or mature research and application, especially in the optimization field.
GSA	Global search, easy execution and implicit parallelism.	Need to be improved in search efficiency and solution precision.
SA	Simple structure, parallel computing, high efficiency, extensive applications and flexible to use; Can converge asymptotically to the global optimal solution; Especially suitable for solving large-scale combinatorial optimization problems.	Slow convergence; time-consuming in computation; Sensitive to parameters; May be constrained by initial conditions.
COA	Simple structure, easy implementation; Short execution time, high execution efficiency; Excellent stochastic searching capability for global optima and robust mechanisms of escaping from local optima.	Dependent on initial values; May not be able or need too much time to find or approximate the optimal solution under unsuitable initial values.
ICA	High convergence accuracy and fast convergence speed; Appropriate for optimization of nonlinear optimization problems with high dimensions.	Relatively low solution precision; Easy to be premature convergent and immersed in local optima.
TS	A global optimization algorithm; Able to escape from local optima; Effective in solving combinatorial optimization problems.	Dependent on initial solutions; Serial but not parallel computation process.
MeA	Combined priorities of global and local search; High search efficiency, fast convergence speed, parallel working manner; Relatively good diversity and fault tolerance ability.	The design of local search module has important influence on solutions.

3.2.2. *Multi-objective optimization performance evaluation indexes*

The solutions found by the multi-objective optimization algorithms are a set of approximate Pareto optimal solutions and we need to evaluate this set of approximate solutions. The evaluation indexes usually involve the following three indexes:

(1) Convergence: the solutions that are most approximate to the Pareto optimal solutions are the best.
(2) Uniformity: the good solutions should be distributed uniformly along the Pareto optimal frontier.
(3) Distribution: the final solutions should cover the whole Pareto optimal frontier as much as possible.

Deb et al. [118] proposed the Convergence Metric index (I_C) to evaluate the convergence performance of the multi-objective optimization algorithms. Schott [119] proposed the Spacing Metric index (I_S).

(1) Convergence Metric: Suppose that the real Pareto optimal solution set distributed uniformly along the ideal Pareto front is $\mathbf{P} = (p_1, p_2, \ldots, p_r)$, and the approximate Pareto optimal solution set searched by the intelligent optimization algorithms is $\mathbf{A} = (a_1, a_2, \ldots, a_s)$. The calculation expressions of the Convergence Metric are as follows:

$$I_C \triangleq \sum_{i=1}^{s} d_i / s \tag{4}$$

$$d_i = \min_{1 \le j \le r} \sqrt{\sum_{k=1}^{m} \left(\frac{f_k(a_j) - f_k\left(p_j\right)}{f_k^{max} - f_k^{min}} \right)^2} \tag{5}$$

wherein, s is the number of searched solutions, r is the number of real Pareto solutions, m is the number of objective functions, d_i is the minimal normalization Euclidean Distance between each searched solution a_i and the real Pareto optimal solution set, f_k^{max} and f_k^{min} are maximal and minimal values in the set **P** of the *k*th objective.

The smaller the value I_C is, the better convergence the algorithm has and the closer to the real Pareto front.

(2) Spacing Metric:

$$I_S \triangleq \sqrt{\frac{1}{s-1}\sum_{i=1}^{s}\left(\bar{d}-d_i\right)^2} \tag{6}$$

$$d_i = \min_{1\le j\le s}\left\{\sum_{k=1}^{m}\left|f_k(a_i)-f_k(a_j)\right|\right\}, \quad a_i, a_j \in \boldsymbol{A}, i,j = 1,2,\dots,s \tag{7}$$

If $I_S = 0$, it denotes that the searched non-dominated solutions in the objective space is distributed evenly spaced.

Moreover, there are also other evaluation indexes like Error ratio (I_{ER}) [120], Coverage of two sets (I_{CS}) [121], Generational Distance (I_{GD}) [122], Hypervolume evaluation index (I_H) [123], ε evaluation index (I_ε) [123], etc.

(3) Error ratio: Error ratio is used to check how many approximate Pareto optimal solutions are covered by real Pareto optimal solutions. The ratio of the number of solutions that are not covered to the whole population is called Error ratio I_{ER}. Thus, if $I_{ER} = 0$, it means that all approximate Pareto optimal solutions are in the real solutions; $I_{ER} = 1$ denotes that all approximate solutions are out of the real solutions.

(4) Coverage of two sets: This index is used to evaluate the mutual coverage rates of two solution sets (A and B) and transfer the coverage rates into a pair of real numbers in [0–1].

$$I_{cs}(A,B) = |\{b\in B|\exists a\in A : a \preccurlyeq b\}|/|B| \tag{8}$$

$$I_{cs}(B,A) = |\{a\in A|\exists b\in B : b \preccurlyeq a\}|/|A| \tag{9}$$

wherein, I_{CS}(A,B) denotes the ratio of solutions in the set B that are dominated by or equal to solutions in the set A. I_{CS}(A,B) = 1 means that B is totally covered by A, I_{CS}(A,B) = 0 means that B is not a little covered by A. 0<I_{CS}(A,B) < 1 denotes that B is partly covered by A. If I_{CS}(A,B) = 1 and I_{CS}(B,A) = 0, then we can say that A is better than B.

(5) Generational Distance: This index describes the distance between the searched Pareto front and the real Pareto front.

$$I_{GD} = \sqrt{\sum_{i=1}^{s} d_i^2}\Big/ s \tag{10}$$

wherein, s is the number of searched solutions, d_i is the Euclidean Distance between the solution and the corresponding real Pareto optimal solution in the objective space. $I_{GD} = 0$ means that the approximate solutions are completely close to the real solutions.

(6) Hypervolume evaluation index: This index is defined as the volume of space that is dominated by the searched solution set but not by the reference point set. It takes into consideration both convergence and diversity.

4. Multi-objective optimization trade-off methods

In order to get a trade-off solution for multiple, conflicting, and non-commensurate objectives, more and more researches have been done on from classical optimization algorithms to intelligent optimization algorithms.

In the past, the earliest and direct method for dealing with multi-objective problems was to transfer them into single objective problems, and then used classical optimization algorithms to solve the problems. In applying this method, we need decide the importance degree of each objective, which is previously determined using a priori method (like Weighted Sum Method) or determined during the search process using the interactive method (like Boundary Intersection Method) [6]. As shown in Fig. 5, there is a summarized demonstration of trade-off methods for solving multi-objective optimization problems.

4.1. A priori methods

There several kinds of a priori methods such as Weighted Sum Method, Constraint Method, Objective Programming Method, Dictionary Ordering Method, Analytic Hierarchy Method and etc.

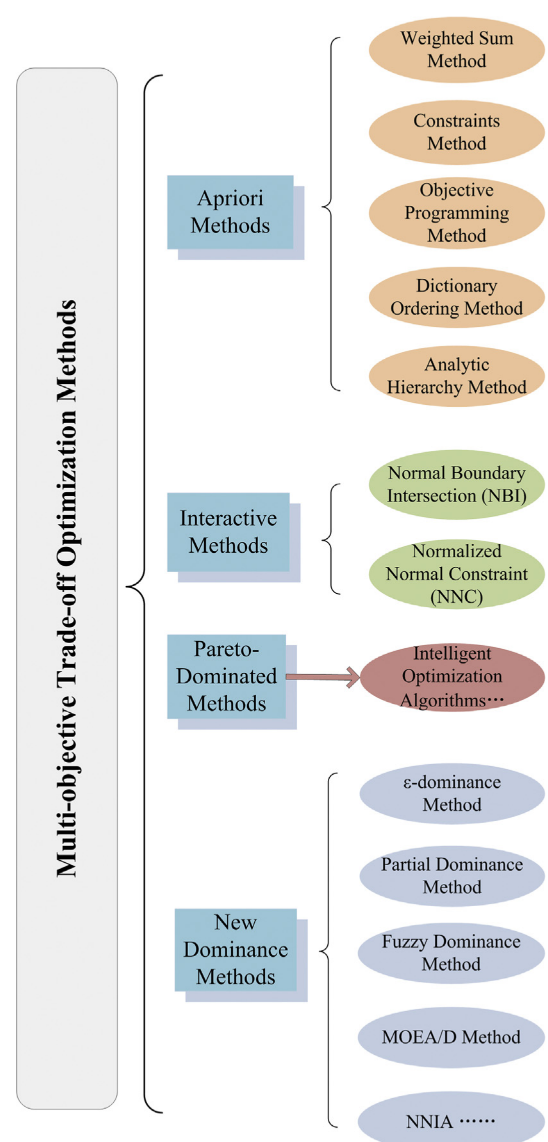

Fig. 5. Classification of multi-objective trade-off optimization methods.

4.1.1. Weighted Sum Method

For m optimization objectives $f_i(\boldsymbol{x})$, $i=(1,2,\ldots,m)$, we use Weighted Sum Method to transfer multiple objectives into one single objective:

$$f(\boldsymbol{x}) = \min \sum_{i=1}^{m} [w_i \times f_i(\boldsymbol{x})] \tag{11}$$

wherein, $w_i \geq 0, \mathrm{i} = (1,2,\ldots,\mathrm{m})$ is a set of weighted coefficients, $\sum_{i=1}^{m} w_i = 1$. Therefore, the multi-objective problem is transferred into a single objective problem, which can be solved by classical optimization algorithms.

The structure of the Weighted Sum Method is so simple that it is easy to understand and apply. However, in this method, decision makers need to decide the weighted coefficients beforehand according to real-world problems or technical experiences.

A variant of the Weighted Sum Method is the Weighted Product Method, which is represented as follows:

$$f(\boldsymbol{x}) = \min \prod_{i=1}^{m} [f_i(\boldsymbol{x})]^{w_i} \tag{12}$$

Xia and Cui et al. [124] proposed a hybrid chaos-PSO algorithm based on sequential quadratic programming (SQP) method (SQP-CPSO), to realize the optimal modeling of the ethylene cracking furnace. The optimized objectives were transformed into one single objective using the WSM according to previous experiences. SQP-CPSO was used to optimize the single objective. The proposed method improved the accuracy of the Kumar model with certain extendable performance.

In order to maximize methanol production and minimize CO_2 emission for a green integrated methanol case (GIMC), Taghdisian et al. [125] proposed an ecological design method for the sustainable development of this methanol production process. The multiple objectives were transferred into one single objective by the weighted product method (WPM), and GA was applied to get the optimal solution.

Ju et al. [126] made performance analyses for a hybrid energy system from aspects of energy, economic, and environment. They used the entropy weight method [127] to calculate the weight coefficients of the objectives so that the multiple objectives were weighted into a single objective. Then the single objective was optimized by the GAMS software.

4.1.2. ε-Constraint method

The ε-Constraint Method was proposed by Haimes et al. [128], which required bounds for each objective function to be decided by experiences.

When applying Constraint Method for dealing with objectives $f_i(\boldsymbol{x})$, $i=(1,2,\ldots,m)$, we select from $f_i(\boldsymbol{x})$ one objective as the optimized objective and the others as constraints of the optimization problem.

$$\min f(\boldsymbol{x}) \Rightarrow \begin{array}{c} \min f_k(\boldsymbol{x}) \\ s.t. f_i(\boldsymbol{x}) \leq \varepsilon_i, 1 \leq i \leq m, i \neq k \end{array} \tag{13}$$

wherein $\varepsilon = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_m]^T$ is the set of upper bounds of estimated objective function values determined by decision makers in advance.

Geng and Cui et al. [129,130] applied COA combining with the constraint method to realize the modeling and optimization of ethylene cracking furnace, which not only improved the accuracy of the model with relatively high computation efficiency, but also improved the energy utilization efficiency of the process.

The advantage of the Constraint Method lies in that it guarantees the objective $f_k(\boldsymbol{x})$ get the ideal value and gives certain consideration the other m-1 objectives $f_i(\boldsymbol{x})$. However, there exist difficulties in setting upper bounds of estimated objective function values. If the upper bounds are too small, the algorithm may not find the feasible solution; or if the upper bounds are too large, the other objectives as constraints may have excessive losses. Thus, the reasonable values of the upper bounds are generally determined according to engineering experiences.

4.1.3. Objective Programming Method

In the Objective Programming Method, decision makers firstly set the desired values of each objective $\boldsymbol{do} = [do_1, do_2, \ldots, do_m]^T$ and add them into the optimization objectives.

$$\min f(\boldsymbol{x}) \Rightarrow \begin{array}{c} \min \sum_{i=1}^{m} \left| f_i(\boldsymbol{x}) - do_i \right| \\ s.t. \;\; x \in \Theta \end{array} \tag{14}$$

The desired values shall be set within the feasible region so as to reach the Pareto optimal solution efficiently. Similarly, it is also difficult to set the desired values. Moreover, the Objective Programming Method is effective in solving linear programming problems but less effective in solving nonlinear complex problems.

Even if these classical methods for dealing with multi-objective optimization problems are simple to use, they can only solve convex optimization problems through coupling multiple objectives based on a prior experience, therefore, these methods are limited for application [131]. Since 1989 when Goldberg [132] firstly introduced Pareto theory in economics into the genetic algorithm, more and more intelligent algorithms and also new dominance mechanisms are proposed and applied to solve multi-objective optimization problems.

4.2. Interactive methods

In order to actively exploit the decision makers' knowledge and experiences, interactive methods were developed, such as the interactive weighted Tchebycheff method [133], the Light Beam Search [134] and the NIMBUS method [135–137].

The interactive methods incorporate preferences of decision makers for each objective during the optimization process. As usual, interactive methods implement an achievement scalarization function (ASF) [138] to generate Pareto optimal alternatives.

There are two widely-applied interactive methods for dealing with multi-objective decision problems: Normal Boundary Intersection (NBI) and Normalized Normal Constraint (NNC) methods. They are relatively new scalarization methods compared with the WSM, which reformulate the multi-objective optimization problem into a parametric single objective optimization problem.

In 1998, Das and Dennis [139] proposed the NBI method, which tackled the multi-objective problems from a geometrically intuitive viewpoint. The method first builds the *convex hull of individual minima* (CHIM) and then constructs (quasi-)normal lines to the plane. The rationale lies in that the intersection between the (quasi-)normal from any point on the CHIM, and the boundary of the feasible objective space closest to the origin is expected to be the Pareto optimal.

The NBI method is able to form a near-uniform spread of the Pareto-optimal frontier, making the NBI a more attractive approach to the Weighted Sum Method in solving non-convex, high-dimensional multi-objective problems.

Ganesan et al. [140] used the NBI interactive method to compromise the multiple optimized objectives in the synthesis gas production process of combined carbon dioxide reforming and partial-oxidation of methane technologies. In conjunction with the

NBI method, the GSA and the PSO algorithms were adopted to realize the process optimization of objectives of methane conversion, carbon monoxide selectivity and the hydrogen to carbon monoxide ratio. The optimization results of these two algorithms were compared using the Euclidean distance metric. The PSO algorithm outperformed the GSA method in terms of uniformity of the Pareto front and computational efficiency.

In 2003, Messac et al. [141] proposed the NNC method, which was similar as the NBI method but combined with features of the ε-constraint method. The ε-constraint method minimizes the most important objective function f_k, while the other objectives are added as inequality constraints with the form $f_i \leq \varepsilon_i$. Based on this idea, in the NNC method, a plane called the utopia hyperplane is constructed through all normalized individual minima, and equally distributed points $\overline{\boldsymbol{f}_p}$ in this hyperplane are determined by consistently varying the weights. Then m-1 hyperplanes are constructed for other objective functions. These hyperplanes are chosen perpendicular to each of the m-1 utopia plane vectors, which join the individual minimum corresponding to the selected objective $\overline{f_k}$. Furthermore, there is an Enhanced Normalized Normal Constraint method (ENNC) proposed in Ref. [142].

Logist et al. [143] incorporated the NBI and NNC methods in a deterministic multiple shooting optimal control to mitigate the drawbacks of the Weighted Sum Method. The combined interactive method was able to obtain an equal distribution along the non-convex Pareto front. It can deal with equality/inequality constraints and boundary value problems, with tight tolerances for global and local optimality. The resulting optimization method is successfully used in the design of a chemical reactor and the control of a bioreactor.

The integration of optimization techniques with these interactive methods were efficiently used to tackle non-convex optimal control problems [144] and applied to different engineering fields [145].

However, NBI and (E)NNC may overlook the extreme parts of the Pareto set. Therefore, Vallerio et al. [146] introduced an Interactive Geometric Extension (IGE) technique to extend the Pareto set for NBI and (E)NNC methods based on geometric considerations. Then the extended NBI or (E)NNC methods were applied successfully to three scalar multi-objective problems and the multi-objective optimal control of a tubular and a fed-batch reactor. The results demonstrated the low computational burden and applicability to higher than three dimensional problems of the proposed methods.

Moreover, Vallerio et al. [147] presented an interactive framework based on NBI and ENNC to realize the nonlinear dynamic multi-objective optimization. By the active use of Pareto Browser Graphical User Interface (GUI), decision makers expressed their preferences via the browsing of scalarization parameters such as *weights*. The parameters were adapted interactively. Finally, the introduced interactive framework for multi-objective dynamic optimization was successfully tested for a three and five-objective fed-batch reactor case study with uncertain feed temperature and heat transfer parameters.

Most interactive methods for multi-objective optimization problems may impair at least one objective function to get a solution. Hence, Miettinen et al. [148] proposed a NAUTILUS method based on the assumptions that past experiences affected decision makers' hopes and decision makers did not react symmetrically to losses and gains. The ability of NAUTILUS to obtain a non-anchored Pareto optimal solution made it an ideal tool to find an initial solution for any other interactive schemes.

In order to deal with the objectives impairment problem, Bortz et al. [149] integrated an algorithm based on a state-of-the-art steady-state flow sheet simulator for designing a distillation process for the separation of an azeotropic mixture. Firstly, a minimal Pareto set with predefined accuracy was calculated by the sandwich approximation method, which can handle non-convexities. Then the decision makers navigated interactively on the Pareto set and explored different optimal solutions by the CHEMASIM tool.

4.3. Pareto-dominated methods

Since 1994 [14], when the NSGA was first used to achieve the Pareto front for the multi-objective optimization problem, intelligent optimization algorithms based on Pareto-dominated methods came up one after another. Intelligent algorithms were able to solve the non-convex optimization problems without coupling objectives, so as to maintain individual features of each objective. More and more researches have been done on intelligent optimization algorithms searching for Pareto-dominated solutions for multi-objective optimization problems.

Combined with the newly emerging chemical reaction optimization algorithm (CRO) [150], the PSO algorithm created new molecules (particles) both used by CRO operations and mechanisms of PSO. The crowding distance method was used to keep the diversity of the Pareto set, which was stored in the external archive. The hybrid optimization method with balancing operators was able to avoid premature convergence and explore more in the search space. (CRO is an optimization technique inspired by the chemical reaction process [151]. It imitates the interactions of molecules in a chemical reaction to reach a low energy stable state.)

Although intelligent optimization algorithms based on Pareto-dominated methods have better performance in convergence, diversity, robustness and flexibility than classical methods, their computation process is sometimes time-consumed and relatively low-efficient [152,153].

Xiang and Zhou [154] proposed a dynamic artificial bee multi-colony algorithm for multi-objective optimization problems, making use of a multi-deme model and dynamic information exchange strategy. In order to accelerate the computation process, the searched non-dominated solutions were stored in an external archive, and the diversity over the archived solutions was maintained by using the crowding-distance strategy.

Chen et al. [155] proposed an adaptive grid particle swarm optimization (AGPSO) algorithm to solve the PID control parameters optimization problem of a hydraulic turbine regulating system (HTRS) under load or unload conditions. Moreover, the fuzzy membership function was used to select the optimal trade-off solution from the Pareto set. The simulation results proved the efficiency and solution quality of the proposed algorithm.

In the optimization procedures, the loss of non-dominated solutions and the appearance of false non-dominated solutions may disturb the solution search process, thus affect the solution accuracy and algorithm performance.

Based on the analysis of these problems, a dynamic multi-objective optimization algorithm (DMOOP) inspired by membrane computing was proposed [156]. DMOOP was applied in the optimal control of a time-varying unstable plant. The key in solving dynamic multi-objective optimization problems lied in constructing discrete, equivalent, and static sub-problems during each time range. The experiment results showed that the proposed method was able to solve optimal control problems effectively, with short rise time, small overshoot and expected output.

Yu et al. [157] proposed a self-adaptive multi-objective teaching-learning-based optimization method (TLBO) called SA-MTLBO. In this method, learners adaptively chose the learning model according to their own knowledge level, performed corresponding search functions to improve the performance of SA-MTLBO. Finally, the proposed SA-MTLBO was applied in the naphtha pyrolysis process to realize the maximization of ethylene, propylene, and butadiene yields, thus improving the energy utilization efficiency of the feed oil (i.e. naphtha).

Niknama et al. [158] presented a multiobjective modified honey bee mating optimization (MHBMO) algorithm to realize the economic and energy optimization of the distribution network. They adopted a fuzzy-based decision maker, according to experiences and preferences, to select the 'best' trade-off solution among the non-dominated optimal solutions.

Zheng et al. [159] proposed a multi-objective group search optimizer method for the power dispatch optimization of a large-scale integrated energy system (LSIES). Meanwhile, a decision making method based on evidential reasoning (ER) [160] was used to determine the trade-off optimal solution from the Pareto-optimal solutions.

Wei et al. [161] proposed a multi-objective interval optimization model to solve the optimization problem of small-scale integrated energy systems. ER was also used in the decision making stage to select the final optimal solution.

Shirazi et al. [162] employed MOGA to solve the simultaneous optimization problem of thermo-dynamic (energetic and exergetic) and economic objectives of an ice thermal energy storage (ITES) system. The final optimal solution was determined using TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) decision making method to reach a reasonable trade-off between objectives.

4.4. New dominance methods

Because the Pareto-dominated methods are not able to simultaneously solve the convergence and distribution problems of optimization algorithms, Laumanns et al. [163] proposed the ε-dominance mechanism. The ε-dominance mechanism is different from Pareto-dominance mechanism in that the former one is based on the idea of hyper grids in space. Afterwards, Hern'andez-Dı́az et al. [164] proposed the combined Pareto-adaptive ε-dominance mechanism. In the mechanism, the ε was a vector whose length was the number of the hyper grids. The values of elements in the vector were related to the geometrical shape of the Pareto front. The values were adjusted self-adaptively according to domination strength information of different parts of the Pareto front.

Later on, Brockoff et al. [165] researched partial dominance. Deb and Saxena [166,167] combined primary component analysis (PCA) method, correntropy PCA method with evolutionary algorithms to solve large-dimensional multi-objective problems. In 2007, Koduru et al. [168] proposed the concept of fuzzy dominance, which used fuzzy dominance function to give weights to each objective function and summed up the weighted objectives.

To deal with uncertain parameters in real-world problems, Singh and Yadav [169] proposed a linear ranking function (the accuracy function) to convert the intuitionistic fuzzy model into a crisp multi-objective nonlinear programming problem. They used a nonlinear membership function with Zimmerman's fuzzy technique, Gamma-operator and Min-bounded sum operator to transfer the multi-objective problem into the single objective problem. The proposed methods were helpful for decision making problems with uncertainty and hesitation, and were able to solve multi-objective optimization problems in production, planning, scheduling and manufacturing systems.

Gharavi et al. [170] utilized the fuzzy logic method in the non-autonomous hybrid green power system (HGPS), to compromise objectives of economics and environmental emission, with different degrees of importance.

Zhang and Li [171] combined evolutionary algorithms with classical multi-objective dealing methods and proposed a multi-objective evolutionary algorithm based on decomposition (MOEA/D) method. The MOEA/D method decomposed the multi-objective problems that approximate the Pareto front into a number of single objective sub-problems, and solved these sub-problems using the evolutionary algorithm. The neighborhood relations between sub-problems were defined as the distances between weighted vectors of sub-problems. The optimization process of each sub-problem was finished by the cooperation between it and its neighboring sub-problem.

Mlakar et al. [172] proposed a surrogate-model-based evolutionary algorithm, called differential evolution multi-objective algorithm based on Gaussian process models (GP-DEMO). The new defined relations with bounding box, instead of Pareto domination, were used to compare solutions under uncertainty. It was able to reduce the error ratio due to the inaccurate surrogate model approximation. By adding the evolutionary algorithm to the surrogate-model, optimal solutions were found, evaluated and used for updating the model.

Some examples of new dominance methods are listed in Table 6 in summary.

5. Application of multi-objective optimization methods in energy saving and emissions reduction

As more and more attention is paid to environmental protection and sustainable development in real-world production and living activities, pollutants emissions, energy efficiency and economic profits become more and more important considerations that should not be ignored in both pure energy-consuming fields and energy production fields (especially of renewable and sustainable energy resources). These considerations start to be simultaneously included as multiple optimization objectives in real-world problems, but not simply summed up as one single optimization objective.

5.1. Application in renewable energy resources production optimization

Unlike other production processes that are aimed at energy utilization optimization, renewable energy resources (RESs) (wind, solar, etc.) production processes are more focused on energy production efficiency, mostly represented by the design

Table 6
Examples of new dominance methods.

New dominance methods	Initially proposed time	Proposer
ε-dominance mechanism	2002	Laumanns, Thiele, Deb, and Zitzler
PCA method	2005	Deb and Saxena
Partial dominance	2006	Brockoff, and Zitzler
Correntropy PCA method	2007	Saxena and Deb
Fuzzy dominance	2007	Koduru, Das, andWelch
MOEA/D method	2007	Zhang and Li
Pareto-adaptive ε-dominance	2007	Hern'andez-Dı́az, Santana-Quintero, Coello Coello, and Molina

optimization of renewable energy systems. Together with economic or environmental objective, the energy efficiency objective gets more and more attention in various renewable resources production processes. These processes include stand-alone energy systems like the wind farm, the power grid or micro-grid, and the biomass production processes, hybrid energy systems or distributed generation networks that integrate kinds of renewables, etc. They are hot or fast developing processes that provide renewables to daily production or living activities and that also attract lots of research interests.

5.1.1. Application in stand-alone energy systems

As stochastic search algorithms are easier to deal with nonconvex and multimodal problems than gradient based classical methods, heuristic algorithms like PSO and GA are used most in multi-objective optimization problems. However, not a single optimization method can be said the best or worst based on one application. For some applications one method may be better than others.

Behera et al. [7] discussed the application of intelligent optimization methods at various modules of a wind farm, in order to maximize the whole power extraction from the wind. Optimization process in each module was undertaken separately, using separate or hybrid intelligent optimization algorithms or combined with classical methods.

For example, in the wind farm layout design process, the paper combined intelligent optimization method and non-linear programming method for this non-convex problem. The global optimal solution was derived from the mathematical programming of the convex sub-region, and the initial solutions of the mathematical programming method were derived through intelligent algorithms. In solving the classical Economic Load Dispatch (ELD) problem, the modified ICA was tested effective with short run time and fast convergence performance. In the past, while solving the ELD problem in the generation scheduling process, classical methods like Lambda Iteration Method (LIM), gradient search method, linear programming, quadratic programming, dynamic programming and Newton-based method, etc. were used [173]. However, ELD for large-scale systems often demonstrated as a highly nonlinear constrained non-convex optimization problem, heuristic intelligent algorithms such as EP, GA, GSA, DE, Adaptive PSO method, Sequential Quadratic Programming (SQP)-combined EP method, GA-SA combined method, etc. were applied [174–177].

For further researches, Rodrigues et al. [93] made a deep discussion on using EAs to solve a Multi-Objective Wind Farm Layout Optimization Problem (MOWFLOP), so as to realize trade-offs between optimization objectives of energy production, capital investment and operational costs. Specifically in solving MOWFLOP, the work studied different characteristics of utilized multi-objective EAs (MOEAs, including NSGA-II) and introduced several constraint-handling techniques. The relation between problem dimensionality/complexity and layout design freedom was also studied, as well as the influence of problem size on algorithms performance. As the state-of-the-art methods for solving multi-objective optimization problems, several MOEAs were discussed and compared performances in solving MOWFLOP. The paper presented a Multi-Objective Gene-pool Optimal Mixing Evolutionary Algorithm (MOGOMEA), which outperformed classical NSGA-II for tested cases and reached trade-off solutions.

Since the electrical grid is very costly for remote locations and diesel power generation produces pollutants into the environment, RESs become more and more popular [178]. Clarke et al. [98] applied the PSO algorithm in the stand-alone renewable energy system to achieve objectives of reducing the total net present cost (NPC) and life-time CO_2 emissions. The optimization result was compared with that from the HOMER software tool. The PSO algorithm used for multi-objective optimization of the system achieved better reduction of the NPC and CO_2 emissions, while realizing effective system size design, and meeting the load demand of desalinated water and electricity. As the scale of the system became large, the advantage of the PSO algorithm over the HOMER tool was more apparent. Moreover, by increasing NPC and CO_2 emissions, a time-varying water profile had more negative effects on the system performance compared to a static water profile.

Cambero et al. [94] pointed out that forest biomass (as a renewable resource) had the potential to substitute fossil fuels in many applications. In the paper presented was a review of studies that assessed or optimized economic, social and environmental aspects of forest biomass supply chains for the production of bioenergy and bioproducts. There was an inevitable trend that integrated these three aspects (measured respectively by production and capital costs, the number of created jobs, and emissions) into a multi-objective optimization problem. The optimal design, planning and management of forest biomass supply chains through multi-objective optimization approaches, based on techno-economic assessments and life cycle assessments (LCA), started to flourish and more practices were needed to testify the performances.

5.1.2. Application in hybrid or integrated energy systems

Since energy crisis and greenhouse effect become increasingly urgent issues all over the world, solar and wind energy come to play important roles in the energy structure with advantages of abundant resources and little pollution. These clean and renewable energy resources are also used to produce or replace or combine with conventional energy resources.

In 2012, Fadaee and Radzi [97] made a review about using EAs for the multi-objective optimization of placement, sizing, design, planning and control problems in hybrid renewable energy systems (HERS). HERS was a green and reliable power system, especially for remote areas. Using MOEAs to reach the trade-offs between different benefits and choosing the prior one based on preferences of decision-makers was realistic and difficult. Most engineering problems considered multiple objectives rather than single one, such as minimizing cost, maximizing performance, and maximizing reliability, etc. They found out that PSO, GA and their variants were most popularly utilized algorithms in HERS which could find global optima.

Efficient utilization of RESs is paid intense attention in order to satisfy energy demands in various aspects of production processes and daily lives [179]. Zheng et al. [159] focused on the research of a LSIES, which integrated distributed district heating and cooling units (DHCs) and RESs (wind) through the power grid. They proposed a multi-objective group search optimizer method with strategies of adaptive covariance [180] and Lévy flights [181] (MGSO-ACL), for the power dispatch optimization of the LSIES. The conflicting optimized objectives included the economic and reliability interests of the power grid and DHCs. Experimental results demonstrated that the MGSO-ACL obtained superior Pareto-optimal solutions in terms of computation time, convergence, solution distribution and diversity with enhanced exploration and exploitation abilities. It was also pointed out in the paper that the proposed method was also applicable for various energy networks including sub-systems, such as micro-grids and distributed energy units interconnected via power grids.

For further researches, Wei et al. [161] proposed a multi-objective interval optimization model and ER method to solve the unit sizing optimization problem of small-scale integrated energy systems. In the paper, the risks related to uncertain wind and solar energies were considered, together with the average life cycle cost (LCC). In order to solve this multi-objective optimization problem, a multi-objective group search optimizer method with adaptive covariance and chaotic search (MGSOACC), which enhanced the adaptability and diversity of the optimizer, was developed. The proposed methods were tested on the direct district heating system (DH) and DHCs with superior search ability, achieving goals of low cost, acceptable risk, and low pollutants emission. It was worth noticing that the variation of daily solar irradiation should be handled carefully, whereas the peak-low-even method was used here to divide the daily heating and cooling loads into three representative periods. The proposed method can be applied to guide the investment behavior of the investors for trade-offs between different interests.

Access to reliable electricity was necessary for improving the living standards. In consideration with assessing the convenience and appropriateness of a hybrid micro-grid system (HMGS) (of the combination of wind, PV (photovoltaic), diesel generator, and battery storage) [99], the trade-off between cost and reliability of the system was the key to assess the system effectiveness and the quality of service. In the paper, a MultiObjective PSO (MOPSO) method was used to find the best configuration of the system and sizing of the components, helping to promote distribution of micro-grid projects and energy access especially in remote areas or developing countries. Since the energy resources were limited in different locations, the optimal ratings of wind, solar, battery, or diesel etc. differed with each other. The proposed method offered a promising way to overcome some technical barriers in the electrification projects.

5.1.3. Application in distributed generation networks

Niknama et al. [158] considered RESs (photovoltaics, fuel cell and wind energy) in the distribution network. They presented a new multiobjective modified honey bee mating optimization (MHBMO) algorithm to realize optimization of total electrical energy costs, electrical active power losses, the voltage deviations, and total emissions of the RESs and the grid. A set of non-dominated Pareto optimal solutions were stored in an external archive called repository, and a fuzzy clustering algorithm was used to handle the varying size of the repository. Standard system tests demonstrated superior exploration ability, feasibility and effectiveness of the proposed algorithm.

As discussed in Ref. [96], different objectives, constraints, and optimization algorithms for the optimal allocation of distributed generators played an important role in improving the accuracy and efficiency of distributed generation (DG) systems. In the paper, objectives that were often selected to be optimized were described and explained, including technical objectives, financial objectives, and combined multiple objectives. Optimization methods of different categories were also presented solving different objectives. Whereas analytic methods or classical numerical methods were used with WSM to form a single objective optimization problem, intelligent optimization algorithms that realized heuristic searches were more applicable for satisfying multiple objectives requirements, resulting in Pareto solutions. Hybrid intelligent algorithms were also introduced for solving the distributed generation optimization problem, often with better results than single algorithms, especially for systems with integrated renewable resources.

Mena et al. [182] introduced a multi-objective optimization based on differential evolution (MOO-DE) framework for the integration of RESs into electric power networks. The framework searched for the optimal size and location of different DG technologies, taking into account both uncertainties/risks related to primary renewable resources availability, power demands, components failures, etc. and the economic concern. Whereas uncertainties were measured by the index DCVaR(CG) (conditional value-at-risk deviation of global cost), the economic performance was measured as the expected global cost (ECG). In the paper, it also expected further extension of the optimization framework, taking technical, social and geographical aspects (e.g. the suitable geographical area for wind turbines and solar photovoltaic) into considerations for trade-offs, too.

It is obvious from previous researches that economic issues are the foremost consideration in most production processes, not only in energy (including RESs and traditional energy such as fuel, coal, natural gas, etc.) production processes, but also in energy-consuming processes. At the same time, environmental issues and even social issues are included as optimization objectives in latest years' researches. There are also continuous focuses on energy related issues such as energy efficiency (either production efficiency or utilization efficiency), energy loss, energy system performance or reliability or stability, etc. Furthermore, performance or technical objectives related to concrete processes or systems may also be taken into account.

The summary of application of multi-objective optimization methods in renewable energy resources production processes is given in Table 7.

As can be seen from Table 7, EAs including PSO, GA, ABC, DE,

Table 7
Applications of multi-objective optimization methods in renewable energy resources production optimization.

Optimization Objectives (energy, economic, environment, technical, social aspects)	Optimization Methods	Optimized System (renewable energy resources)	Authors
energy production, capital investment, and operational costs	EAs, a review	wind farm layout optimization problem	Rodrigues, Bauer, Bosman, 2016
NPC and life-time CO_2 emissions	PSO	stand-alone renewable energy system	Clarke, Al-Abdeli, Kothapalli, et al., 2015
production and capital costs, emissions, and the number of created jobs	EAs, a review	forest biomass supply chains	Cambero, Sowlati, 2014
energy reliability and economic interests	MGSO-ACL; ER: decision-making method	LSIES	Zheng, Chen, Wu, et al., 2015
renewable energy sources risks and average LCC	MGSOACC; ER	small-scale integrated energy systems	Wei, Wu, Jing, et al., 2016
renewable energy reliability and costs	MOPSO	hybrid micro-grid system	Borhanazad, Mekhilef, Ganapathy et al., 2014
total electrical energy costs, total emissions, electrical active power losses, and voltage deviations	MHBMO	integrated distribution network	Niknama, Kavousifard, Tabatabaei, et al., 2011
financial, technical objectives, a review	intelligent optimization algorithms	DG systems	H.A., Huy, Ramachandaramurthy, et al., 2016
renewable energy sources uncertainties/risks, the economic concern, power demands, and components failures	MOO-DE	integrated electric power networks	Mena, Hennebel, Li, et al., 2016

COA, and their variants in improved forms are utilized in real-world renewable energy production processes for multi-objective optimization of economic, energetic, environmental or technical issues. Actually, other intelligent algorithms can also be applied to these problems as long as they meet the demands of decision-makers in computation efficiency, solution precision or diversity, etc. Users can further improve intelligent algorithms with different optimization techniques to make them more suitable for solving concrete problems.

5.2. Application in energy saving optimization

As mentioned above, energy and environment issues are also crucial considerations in nowadays energy-consuming processes. Except for cases considering only technical objectives that were introduced in Chapter 3 and Chapter 4, we will present cases that take energy and/or environment issues into account of the multi-objective optimization and try to find trade-off optimal solution.

The energy issue, together with economic, environment or technical issues, is important for sustainable development and planet protection not only in production processes, but also in living activities like building design or retrofitting. These processes aim at either improving the energy (utilization) efficiency or reducing the energy consumption.

5.2.1. Application in living activities

In United States of the America (USA) in 2010, 41% of the total primary energy and 74% of electricity is consumed by residential and commercial buildings. Meanwhile, these buildings also produce about 54% of SO_2, 40% of CO_2, and 17% of NO_x emissions in energy consumption processes [183]. The current energy trends that raise great concerns are defined by the International Energy Agency as "three Es": energy security, environment and economic prosperity [184]. Not only in USA and the European Union (EU) [185], but also around the whole world, people start to give priority to the optimization of energy consumption in building. Therefore, in building design processes, the environmental effects as well as energy efficiency are important considerations, too. Several studies have focused on developing design methods both energy-efficient and environmental-friendly [186–188].

Fesanghary et al. [189] aimed at the energy efficiency and environmental performance improvement of buildings. They used the EnergyPlus tool to model the whole energy system of the building, and applied HS to solve the optimal design problem. The model aimed to realize energy consumption optimization, financial costs reduction and decrease of environmental impacts (represented by LCC and CO_2 equivalent emissions). Furthermore, the proposed method was validated efficient on a typical single-family house in the southern part of USA. Moreover, in the paper discussed were a series of identified Pareto optimal solutions, which helped designers better understand the trade-off relation between economic and environmental performances.

The retrofitting of buildings was important not only in improving occupants' comfort and health, but also in reducing the energy consumption and green-house gasses emissions. Hence, Asadi et al. [103] combined GA with ANN to establish the multi-objective optimization model for building retrofitting projects. Taking advantage of rapidity of ANN and optimization ability of GA, conflicting objectives of energy consumption, retrofit cost and thermal discomfort were optimized. They took a school building as a case to take individual optimization of each objective, and then simultaneous multi-objective optimization to survey the practicability and performance of the proposed method. During the experiments, the competitive interaction between objectives and the influence of decision variables on each objective or even the building performance was also analyzed. At last, the authors also looked forward to assessing uncertainty factors in the future.

5.2.2. Application in production processes

Because most production processes consume different kinds of energy resources (both traditional and renewable energy resources), energy utilization optimization constitutes a crucial part of cost saving and environment protection.

5.2.2.1. Application for renewable energy utilization optimization. A systematic procedure based on the geographical information system (GIS) for the multi-objective optimization of the energy system was presented by Fazlollahi and Becker et al. [190]. The systematic procedure included optimal process design and operation of the energy distribution network and integration techniques for energy and resources transportation. Multi-objective optimization of the energy system has been achieved through various optimization techniques, such as GA [191]. A multi-objective multi-period optimization model consisting of process design and energy integration techniques was described in the previous works [192,193]. Then an improved multi-objective multi-period optimization methodology was developed, which was split up into four main stages: master optimization, thermo-economic simulation, slave energy integration optimization and environ-economic evaluation. In the master optimization stage, the evolutionary algorithm was used to realize the simultaneous optimization of system efficiency, overall CO_2 emissions and the total annual cost (TAC). In the slave energy integration optimization stage, the problem was concluded as a mixed integer linear model. The model determined the best resources schedule of selected subsystems to meet the requirements at a minimum cost, which was solved by robust linear programming methods.

Along with the rapid increase of world population and energy consumption, the effective utilization of renewable resources and low temperature waste heat has gained much attention. Feng et al. [108] used NSGA-II to realize thermo-economic multi-objective optimization, which involved both thermodynamic performance and economic factors. The algorithm was applied in the optimization processes of regenerative organic Rankine cycles (RORC) and basic organic Rankine cycles (BORC), which were advanced technologies for converting low-grade heat resources into power [194]. The optimization objectives were concluded as the maximization of exergy efficiency [195] and the minimization of levelized energy cost (LEC) [196]. Based on the importance analysis of key operation variables to optimization objectives, the bi-objective optimization of RORC and BORC was conducted with favorable performances. The results showed that both the exergy efficiency and the LEC of RORC were higher than those of BORC. It was because that the higher exergy efficiency and thermodynamic efficiency led to lower net power output and worse economic performance. On the basis of engineering experiences, a decision making process was conducted by a hypothetical point. In other words, the nearest point in the Pareto frontier to the ideal point was chosen as the desired and defined as the final Pareto-optimal solution. Furthermore, maximizing the net power output was added as the third optimization objective and the proposed algorithm was successful to find Pareto optimal solutions.

Naserian et al. [107] applied a controlled elitist NSGA-II to realize the multi-objective ecological optimization of a regenerative Brayton cycle [197]. Based on finite-time thermodynamic analysis [198] and exergy analysis in finite-size components [199], the net output power and ecological states of the cycle were to be maximized, while the total exergy destruction was minimized by introducing a dimensionless parameter, which embeds the time variable. The utilized controlled elitist NSGA-II was tested with better convergence property and distribution of solutions than the original NSGA-II. The multi-objective optimization results provided not one optimum point but a range of optimum ones, satisfying a reliable and adoptable system even under variable daily power demand.

Solar energy, as a promising type of renewable resources, has been utilized as energy input for Brayton type gas turbines for electricity generation [200,201]. Based on previous works [202,203], Sánchez-Orgaz et al. [109] applied the NSGA-II to solve the multi-objective multi-parameter optimization problem of the recuperative multi-step solar-driven Brayton thermo-solar plant. The optimized objectives involved the power output and the overall thermodynamic efficiency of the thermo-solar plant, which were normalized by distance methods. Based on the thermo-dynamic analytical model of the plant, key design variables were recognized. Moreover, several configurations including ideal, realistic, single-stage or multi-step of the plant were analyzed and optimized. The paper also applied different decision making approaches (i.e. Fuzzy, LINMAP, TOPSIS, Bellman-Zadeh, Ideal point and Non-ideal point approaches) and made comparisons between the optimal solutions. Seeing from the acceptable optimization results physical insights were obtained by the multi-criteria decision method.

Ju et al. [126] constructed a hybrid energy system based on a combined cooling, heating and power (CCHP) system driven by distributed energy resources (represented by natural gas, solar energy and wind energy) (DERs CCHP). The optimized energy, economic and environmental objectives of the energy system were respectively expressed as energy rate, total operation cost (TOC), and carbon dioxide emission reductions. Experiments were conducted for mono-objective optimization of each optimization objective and multi-objective optimization of all three objectives based on the entropy weight method, comparatively on the hybrid system and CCHP system driven solely by natural gas (NG CCHP) in Guangzhou Higher Education Mega Center in China. The optimization results showed that the multi-objective optimization could balance three optimization objectives and accommodate different electric, cooling and heating loads. Moreover, the optimal solutions and performances of DERs CCHP were better than those of NG CCHP.

5.2.2.2. Application for traditional energy utilization optimization. Shirazi et al. [162] made thermal (energetic and exergetic), economic, and environmental (emissions cost) analyses of an ITES system for gas turbine cycle inlet air cooling. In the paper, a MOGA was employed to solve the simultaneous optimization problem of thermo-dynamic and economic objectives. The optimized objectives were measured respectively by exergetic efficiency and the total cost of the system, including the capital, maintenance and operational costs (including the costs of electricity and fuel consumption) and the social cost of emissions. Moreover, the optimal results achieved by utilizing the multi-objective method were compared with those by the single objective method considering each of the mentioned objectives. The results demonstrated that the multi-objective optimization provided a reasonable trade-off between objectives. There was another important factor for assessing the system to be covered: the payback period for the installation investment. The additional costs would be compensated over this period with the income received from the optimized system.

Yousefi et al. [102] proposed a PSO algorithm based on learning automata (LAPSO) to solve the design optimization problem of real-world compact heat exchangers (CHEs) [204] with varying heat duties. The LAPSO algorithm was implemented to deal with changing design variables and operation conditions, so as to get the trade-off solution between cost savings and thermodynamics efficiency. LAPSO integrated with learning abilities through receiving favorable feedbacks from the environment gained extra flexibility and exploitation abilities. In handling equality and inequality constraints, an efficient and user-friendly feasibility based ranking strategy (FBRS) was applied. The numerical results showed that the proposed algorithm was reliable with better solutions with robustness, compared with methods like GA or PSO. The proposed method was illustrated on a plate-fin heat exchanger but was applicable for all types of heat exchangers.

Based on previous researches [129,130,205], Geng et al. [100] proposed an adaptive MOPSO (AMOPSO) algorithm for the optimization of the ethylene cracking furnace, referring to DEA (data envelopment analysis [206])-based energy efficiency analysis [207,208]. The optimization objectives involved maximizing product yields of ethylene and propylene, and minimizing consumption of energies (i.e. the feedstock naphtha and steam). Besides, the fuzzy consistent matrix method was used in the decision-making process. The AMOPSO, compared with classical intelligent algorithms, produced superior convergent and distributed solutions with consistency in solving different problems. An ethylene cracking furnace case was optimized using the proposed algorithm to reach a viable balance between economic and energy considerations. Decision makers then chose the trade-off Pareto solution catering to their preferences by fuzzy evaluation.

The summarization of application cases of multi-objective optimization methods in energy saving related fields is given in Table 8.

It can be seen from Table 8 that EAs (like GA, PSO, HS and their variants, etc.) make good effect in multi-objective optimization of renewable and traditional energy production or utilization processes, taking into consideration of energy, economic, environment or technical issues. Different processes make different models with various system features like non-linearity, multi-modal, and maybe non-convexity. Making use of advantages of each intelligent optimization algorithm with effective dealing strategies helps to solve different problems efficiently.

5.3. Application in emissions reduction optimization

In addition to economics, energy and reliability, environmental issues are also of great importance for the optimal design, construction, production, use, or transportation of various activities around us people. Emissions (composed mainly of greenhouse gases emissions) reduction is also linked closely with the protection of our planet, both in living activities and production processes.

5.3.1. Application in emissions reduction

In order to minimize the operation cost and the environmental impact (gaseous emissions) of a micro-grid, Chaouachi et al. [95] formulated a multi-objective intelligent energy management framework (MIEM), using artificial intelligent algorithms together with the linear-programming method. In dealing with constraints, the Artificial Neural Network Ensemble (ANNE) based on regularized negative correlation learning (RNCL) was used to forecast renewable energy resources generation (photovoltaic and wind power generation) and load demand. A fuzzy logic expert system was used for battery scheduling with uncertainties, as a part of online energy optimization. The proposed machine learning characterized with enhanced learning and generation abilities was successful in minimizing the operation cost and the emission level. The framework was finally implemented on a micro-grid simulation model, and its effectiveness of solving competing objectives was validated.

Zhang et al. [101] proposed a bare-bones multi-objective

Table 8
Applications of multi-objective optimization methods in energy saving.

Optimization Objectives (energy, economic, environment, technical, social aspects)	Optimization Methods	Optimized System	Authors
energy efficiency, LCC, and CO_2 equivalent emissions	HS	residential building	Fesanghary, Asadi, Geem, 2012
energy consumption, retrofit cost and thermal discomfort	GA with ANN	building retrofitting projects	Asadi, da Silva, Antunes, et al., 2014
system efficiency, TAC, and overall CO_2 emissions	EA	energy distribution network	Fazlollahi, Becker, Marécha, 2014
exergy efficiency, LEC, and the net power output	NSGA-II	RORC and BORC	Feng, Zhang,Li, Shi, 2015
total exergy destruction, ecological states of the cycle, and net output power	GA	regenerative Brayton cycle	Naserian, Farahat, Sarhaddi, 2015
overall thermodynamic efficiency and power output	NSGA-II	multi-step solar-driven Brayton plant	Sánchez-Orgaz, Pedemonte, Ezzatti, et al., 2015
energy rate, total operation cost (TOC), and CO_2 emissions	the entropy weight method, GAMS	hybrid energy system based on CCHP	Ju, Tan, Li, et al., 2016
exergetic efficiency and total cost(the capital, operational costs, and the social cost of emissions)	MOGA; TOPSIS: decision-making method	ITES	Shirazi, Najafi, Aminyavari, et al., 2014
thermodynamics efficiency and cost savings	LAPSO	CHEs	Yousefi, Darus, Yousefi, et al., 2015
naphtha and steam consumption, product yields	AMOPSO	ethylene cracking furnace	Geng, Wang, Zhu, Han, 2016

particle swarm optimization (BB-MOPSO) algorithm to solve the optimization problem of environmental/economic dispatch (EED). To handle the EED problem with conflicting objectives, many evolutionary algorithms were proposed [209–211], as well as the multi-objective mathematical programming method [212]. The variants of PSO such as the multi-objective chaotic PSO were developed to solve the multi-objective EED optimization [213,214]. The BB-MOPSO algorithm was distinctive in that it needed not tune up control parameters. Some other techniques such as constraint handling strategy, external archive storing elite particles and the crowding distance method were used to make the BB-MOPSO algorithm more effective in solving the multi-objective optimization of fuel cost and pollutants emissions. Moreover, the fuzzy membership function was used to present preferences of decision makers to select the trade-off solution from the Pareto optimal solutions. The simulation results showed that the proposed algorithm efficiently produced well-distributed solutions approximating the real Pareto set with good performance in a short running time and it can be extended to other optimization problems with good robustness.

Water distribution networks are complex systems which require high investment in construction and maintenance. Moreover, the optimal design problem of water distribution networks is a multi-objective difficult problem. Several works explored to solve the problem in which the objectives are cost minimization and reliability maximization [215,216]. Herstein et al. [217] tried to assess the environmental impact of water supply systems. Based on the previous work which presented a methodology to evaluate the carbon emissions in the whole life cycle [218], Marques et al. [219] combined a multi-objective SA algorithm with a hydraulic simulator to realize the optimal design and operation of water distribution networks. The combined method was used to optimize the total cost calculated as the sum of investment, operation and energy costs, environmental impacts as life cycle carbon emissions, energy consumption related emissions, and pressure violations. Moreover, the decision tree was used here to describe the Pareto optimal set, assisting decision makers to select the optimal solution according to certain preferences. The optimization results showed that the proposed method was able to deal with conflicting objectives, environmental impacts and future uncertainty.

The strict environmental regulations on sulfur and aromatic compounds emissions made the hydro-treating process of diesel fuel become more and more important. A multi-objective optimization method based on NSGA-II was applied in a simulated hydro-treating reactor to search for the optimal operational condition, which was represented by minimal sulfur and aromatic compounds emissions [106]. The simulation model was realized by a heterogeneous model of three main reactions: hydro-desulfurization, denitrogenation, and dearomatization. The effects of key operational parameters such as temperature, pressure, liquid hourly space velocity, and H_2/oil ratio on hydro-treating reactions were also evaluated, serving as guidance for the multi-objective optimization.

5.3.2. Application in ecological design

Due to the growing awareness of the importance of protecting the environment, concepts like green design, ecological design, environmental benign design, cleaner production, etc. have been proposed and used to realize the sustainable development of production processes [220]. Taghdisian et al. [125] proposed an ecological design method for sustainable development of methanol production. In the paper, a green integrated methanol case (GIMC) was presented and compared with the classical reference methanol case (RMC). The environmental performances and operational variables of both cases were evaluated, using the life cycle assessment (LCA) method. CO_2 was recognized as the main emitted pollutant in the methanol production (while other pollutants involved CO, NO_x and VOCs, etc.). Multiple objectives of maximizing methanol production and minimizing CO_2 emission in the GIMC were then optimized by GA to get optimal solutions with acceptable level of diversity, offering economically and environmentally desirable design options. (LCA is a systematic methodology in which the environmental impacts are considered in the product total life cycle [221,222].)

For optimally designing the hybrid green power generation systems (HGPS), Gharavi et al. [170] utilized the ICA to get the trade-off solution between economic and environmental objectives, in consideration with reliability. The system was consisted of photovoltaic arrays, wind turbine units, fuel cell and electrolyzer. The ICA was verified as an algorithm with high convergence accuracy, and was appropriate for optimization of high-dimensional nonlinear HGPS with large number of variables and discontinuity features. The optimization results of non-autonomous HGPS were also compared with those of autonomous HGPS.

Fazlollahi and Mandel et al. [223] researched the optimal design and operation of energy systems so as to reach the balance between energy supply and demand. They firstly presented a multi-period energy system optimization (ESO) model with a single objective function, making use of mixed integer linear programming (MILP) methods. Then, a multi-objective optimization method based on the evolutionary algorithm (EMOO) was presented. Integrating EMOO into the ESO model, a multi-objective investment and operating optimization methodology was formed for the whole complex energy system. The methodology included master and slave optimization stages. In the master optimization stage, the EMOO method was performed to optimize annual investment, operation costs and CO_2 emissions with a population of viable solutions. Based on the integer cut constraints (ICC) and ε-constraint methods concerning respectively integer and continuous variables, the MILP was used in the slave optimization stage to optimize the mono objective of the total cost in short resolution time. It was pointed out in the paper that the resolution time of EMOO was possible to be improved via parallel computing.

Tamilselvi and Baskar [105] applied a covariance matrix adaptation evolution strategy (CMA-ES) [224] to realize the optimal transformer design (TD) problem [225], which was multi-modal, multi-objective, mixed-variable and non-linear. The proposed CMA-ES method was used to minimize individually mono objectives of the purchase cost, the total life-time cost, the total mass and the total loss, in combination with penalty parameter less constraint handling strategy. The optimal design results on three cases of CMA-ES were better than those of conventional design procedure, branch and bound algorithm, self-adaptive differential evolution or real coded genetic algorithm (RGA), either in global search ability, solution accuracy or consistency. Moreover, based on the previous practices, NSGA-II was applied to realize multi-objective TD optimization of the four objectives simultaneously to get a diverse set of solutions. The best trade-off solution chosen then by fuzzy set theory was better than that obtained by CMA-ES in mono objective optimization.

Groot et al. [226] proposed a FarmDESIGN model to realize reconfiguration optimization of mixed farming systems, as well as meet farm and policy constraints, which was complicated with interrelated large array of components. The FarmDESIGN model evaluated the productive, economic and environmental performance of the farm by coupling a bio-economical farm model, and generated a set of feasible non-dominated Pareto solutions. Moreover, the Pareto-ranking and crowding distance methods were used to select from feasible solutions. By using the Pareto-based DE algorithm, objectives of maximizing operating profit and organic matter balance, minimizing labor requirement and soil nitrogen losses were optimized along the trade-off front. The proposed approach was finally testified on a realistic mixed organic farm in the Netherlands and produced a collection of alternative design options. It was also generic with the potential to support the learning and decision-making processes of farmers, farm advisers or scientists.

Schwartz et al. [104] pointed out that early design was shown to significantly impact the energy performance of buildings. The refurbishment of existing buildings was considered a cost-effective way to the reduction of the life cycle environmental impact. Based on the LCA of the buildings, the LCCF (life cycle carbon footprint) and the LCC over an assumed life span of 60 years were minimized. These two objectives were calculated based on the analysis of Life Cycle Energy use (LCE), consisted mainly of the embodied energy required for construction, maintenance and refurbishments, and operational energy used for maintaining the environmental and thermal conditions within the building. Thus the LCCF was computed as the embodied costs and CO_2 emissions, and the LCC as operational costs and CO_2 emissions. The multi-objective optimization was realized by the computational efficient MOGA, which was one of the most widely used methods in the optimization of building performances. Further, the CO_2 payback time was calculated and the impact of building orientation on objectives was examined.

The summarization of application cases of multi-objective optimization methods in emissions reduction is listed in Table 9.

Adding or transferring to the environment objective, EAs are still able to solve the multi-objective optimization problems in living activities and production processes (including energy systems, complex systems, agricultural and industrial production). Up till now, GA and PSO algorithms or their variants in improvement (like NSGA-II) are still popular in real-world applications. Intelligent algorithms like ES, SA, ICA, etc. are also researched and applied with satisfied optimization results. Nowadays, more and more algorithms, progressing with more powerful and applicable abilities, are put into use in realizing multi-objective optimization of real-world problems. Due to the limitation of the length of the paper, we could not cover all researches about different optimization issues in every field. However, various optimized objectives and systems have more or less the same problem features that can be solved by choosing or improving effective intelligent algorithms.

6. Current difficulties and future directions for researches

Although there are already many researches and continuous developments about methods for solving multi-objective problems, there still exist difficulties to be solved or performance to be improved.

Table 9
Applications of multi-objective optimization methods in emissions reduction.

Optimization Objectives (environment, economic, technical, social aspects)	Optimization Method	Optimized System	Authors
emission level and operation cost	artificial intelligent algorithms, machine learning	micro-grid	Chaouachi, Kamel, Andoulsi, et al., 2013
pollutants emissions and fuel cost	BB-MOPSO	EED problem	Zhang, Gong, Ding, 2012
life cycle carbon emissions, energy consumption related emissions, total cost, and pressure violations	SA	water distribution networks	Marques, Cunha, Savić, 2015
sulfur and aromatic compounds emissions	NSGA-II	simulated hydro-treating reactor	Ani,Ebrahim, Azarhoosh, 2015
CO_2 emission and methanol production	GA, WPM	GIMC	Taghdisian, Pishvaie, Farhadi, 2015
environmental emission and economics	ICA	HGPS	Gharavi, Ardehali, Ghanbari-Tichi, 2015
CO_2 emissions, annual investment, and operation costs	EMOO	multi-period energy system	Fazlollahi, Mandel, Becker, 2012
total life-time cost, total mass, total loss, and purchase cost	CMA-ES and NSGA-II	distribution TD	Tamilselvi, Baskar, 2014
LCCF and LCC	MOGA	refurbishment of existing buildings	Schwartz, Raslan, Mumovic, 2016

(1) The first-of-all important aim of multi-objective optimization methods is try to generate a set of well converged and uniformly distributed non-dominated optimal solutions. The convergence rates are also important. For different intelligent algorithms, it is helpful to utilize different techniques in algorithms according to their distinct features. If we are able to improve these algorithms from their intrinsic theorems and concepts, so as to make them more suitable for solving multi-objective optimization problems, the optimization results will be more desirable.
(2) Unlike single-objective optimization, multi-objective optimization problems do not produce only one single solution, thus maintaining a diverse solution set keeps an important consideration. Diversity of non-dominated solutions provides more selections for decision makers and helps to prevent from solution losses. It is worthy to be noticed that we should try to escape from local optimum solutions and find global optima. In order to maintain the diversity and accelerates the algorithm speed, the external archive is used by many algorithms. The elitism ensures that the best solutions will not be lost.
(3) As an essential issue that is always under improvement, the computation complexity remains to be reduced, computation time shortened and computation efficiency improved. On the other hand, the formulation of an efficient and evidential stop criterion of multi-objective optimization methods is difficult to realize. Judging the advance of optimization is as complex as the multi-objective optimization problem itself. Therefore, the optimization process stops when it reaches a given number of iterations or function evaluations.
(4) Most of the multi-objective optimization methods and the software tools are for analysis, guidance and planning, but in real-time application where the action should be taken dynamically within seconds, the considerable computational time is a disadvantage. The key of the dynamic or on-line multi-objective optimization is the construction of discrete, equivalent and static sub-problems during each time period. How to express preferences of decision makers and share their information to appropriately steer the decision process is helpful in real-world optimization. Meanwhile, parallel computation will be appealing for lowering the computational burden.
(5) When it comes to many-objective optimization problems with more than three objectives or high-dimensional optimization problems, the optimization becomes more complicated and the computation complexity increases exponentially. Decompose these problems effectively into sub-problems or use dimensionality reduction technique without losses of solutions make the key point, which is also the difficult part.

As for the application in energy saving and environment protection fields, there are some concrete points need to be focused on:

(1) Because each multi-objective optimization problem in application is unique with distinct features, the optimized objectives, applied intelligent algorithms and trade-off methods for decision making, constraints and handling techniques are varied. As usual, there is no standard or benchmark to evaluate the performance of application optimization results. As long as the multi-objective optimization method finds the optimal solution set and the final trade-off solution, satisfying all constraints and making a compromise between objectives without harm to any one objective, the optimization method is said to be effective and the solution reasonable. The result comparison could be made only between different algorithms or trade-off methods for the same process with same objectives, constraints, etc. However, each attempt to utilize an intelligent algorithm and trade-off method often takes considerable time and efforts. How to select the optimization algorithm and trade-off method for concrete multi-objective optimization problems often relies mostly on expert knowledge or production experiences in this field and previous researches existed.
(2) Operational costs or investment or product profits are the most obvious important concern in most production processes and are relatively easy to be evaluated using LCA for example. Besides technical objectives that are related to each distinct real-world optimization system or process, which is characterized with different features, energy considerations (such as energy efficiency improvement or energy consumption reduction or energy saving potential, etc.) and environment considerations (i.e. greenhouse gases emissions reduction, which is composed mainly of carbon dioxide) are gaining more and more attention. For energy considerations, we need some support methods or tools to quantify them, such as energy or exergy analysis, energy balance or transfer equations expression, etc.
(3) There are generally two ways to satisfy multiple objectives in one optimization process: using the weight coefficients in the WSM or WPM method or other a priori methods to transfer the multi-objective optimization problem into a single objective optimization problem, which can then be solved by numerical or heuristic methods; applying appropriate intelligent optimization algorithms to realize simultaneous optimization between objectives and decision making methods to achieve the trade-off. With different focuses on optimized objectives, the optimization results offer differ with each other. By incorporating the local search technique into the optimization algorithm, we could achieve fast convergence without loss in diversity. The comparison between independent optimization of each single objective and multi-objective optimization could offer some useful advices for optimization potential of each objective.
(4) When it comes to more than three objectives for most nonlinear and large-scale (and even non-convex) real-world optimization problems, the optimization processes become more complicated. Some techniques of dimensionality reduction, problem decomposition, constraint handling, and convexification, etc. are utilized to simply the complex optimization problem without losses of solutions as much as possible.

In the future, we will also carry out experiments on utilizing some state-of-the-art tested effective intelligent optimization algorithms (such as NSGA-II, SPEA2, MOPSO, NNIA, and PESA-II, etc.) with trade-off methods in solving multi-objective optimization test functions. We will further take the real-world ethylene cracking furnace as the example to verify the experiment results, with objectives of maximizing products yields of ethylene, propylene etc., minimizing energy consumption and CO_2 emissions, etc.

7. Conclusion

Most real-world problems are intrinsically multi-objective optimization problems, including design, scheduling, modeling, and optimization problems, etc. The optimized objectives range from materials or feedstock consumption, production, operation and maintenance cost, capital and investment, product yields, product quality indexes, and profits, to energy efficiency or exergy efficiency or energy consumption, to pollutant emissions (mainly greenhouse gases emissions) such as CO_2, SO_2 emissions etc. One of the biggest difficulties in solving multi-objective optimization problems lies in the trade-off among different conflicting and synergetic objectives. When we find a solution that makes one objective optimal, it may leads another objective or other objectives to fall into bad results. Since the multi-objective problem was firstly proposed, more and more researchers have made efforts to solve the problem with effective methods, producing acceptable optimal solutions.

In this paper, the description of multi-objective optimization problems and solutions definition is given in summary. Due to the complexity, orthodox and mostly nonlinearity of multi-objective optimization problem, intelligent optimization algorithms like evolution based and swarm based algorithms were proposed and has been improved continuously for solving the problem with good performance. We also give a brief introduction of some most often used intelligent optimization algorithms about their development processes and (dis)advantages. Some existing test problems consisted of mathematical functions are also demonstrated and the relative performance indexes for verifying the effectiveness of multi-objective optimization methods are summarized.

In order to get a final optimal solution for specific multi-objective problems, trade-off optimization methods including a prior methods, interactive methods, Pareto-based methods and new dominance methods were proposed and improved. In the Chapter 4, details about these trade-off methods are described. Meanwhile, applications of these trade-off methods in solving multi-objective optimization problems are also taken as examples.

At last, applications of multi-objective optimization methods in solving real-world multi-objective optimization problems, which aimed at multi-objective optimization of economic, energetic, environmental, technical, and social concerns, are demonstrated. The real-world problems include both energy (especially RESs) production and energy consumption processes. These applications can serve as guidance for solving multi-objective optimization problems in real-world production processes, making use of appropriate optimization algorithms and trade-off methods for simultaneous optimization of costs, energy efficiency or energy consumption, environmental emissions, technical aspects or social effects.

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Nomenclature

A	approximate Pareto optimal solution set
d_i	normalization Euclidean Distance between each searched solution and the real Pareto optimal solution
do_i	desired value of each objective
f_i	objective function
$\overline{f_k}$	normalized objective function
G	number of generations
I_C	convergence metric index
I_{CS}	coverage of two sets
I_{ER}	error ratio
I_{GD}	general distance
I_H	hypervolume evaluation index
I_S	spacing metric index
I_ε	ε evaluation index
m	number of objectives
n	number of decision variables
N	population size
$\overline{N}$	external population size
P	real Pareto optimal solution set
p	number of inequality constraints
q	number of equality constraints
r	number of real Pareto solutions
s	number of searched solutions
x	decision vector
y	objective vector
x_i	the *i*th decision variable
y_i	the *i*th objective

Greek letter

ε	set of upper bounds of estimated objective function values
ε_i	upper bound of *i*th objective function value
w_i	a set of weighted coefficients
Θ	parameter space of decision vector
Ψ	objective space
Ω	feasible domain of all feasible solutions

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